Investigating the origins and significance of low-frequency modes of climate variability

Myles R. Allen
Department of Physics, University of Oxford and Rutherford Appleton Laboratory, U.K.

Leonard A. Smith
Mathematical Institute, University of Oxford, U.K.

Abstract. An analysis of the 130-year record of the Earth’s global mean temperature reveals a significant warming trend and a residual consistent with an autocorrelated (“red”) noise process whose predictability decays with a timescale of two years. Thus global temperatures, in isolation, do not indicate oscillations at 95% confidence against a red noise null hypothesis. Weak signals identified in the global series can, however, be traced to significant sea surface temperature oscillations in the equatorial Atlantic (period \( \sim 10 \) years) and the El Niño region of the Pacific (3–5 years). No robust evidence is found in this data for interdecadal oscillations. The 10-year Atlantic oscillation corresponds to a pattern of temperature anomalies which has been associated with interannual variations in West African rainfall and in U.S. hurricane landfall frequency.

Testing against red noise in SSA

When analysing complex systems, we must allow for noise (or processes indistinguishable from noise) being autocorrelated in time. The simplest discrete autocorrelated noise is the AR(1) process [Davis & Vinter, 1985]:

\[
u_{t+1} = \gamma u_t + \alpha z_t\]

(1)

where the first term on the RHS represents the memory of the process, and \( z_t \) is a white noise (independent, uniformly distributed) forcing. \( \gamma \) and \( \alpha \) are real coefficients. The power spectrum of AR(1) noise contains no spectral peaks, although it is biased towards low frequencies (i.e. “red”). Predictability decays exponentially with a time-constant \( \tau = -[\ln(\gamma)]^{-1} \). A variety of systems, both deterministic and stochastic, generate red power spectra, so processes like AR(1) noise must be considered in evaluating evidence for trends or oscillations in climate data.

Singular Spectrum Analysis, or SSA [Broomhead & King, 1986; Fraedrich, 1986; Vautard & Ghil, 1989], extracts information from a discrete scalar time series by finding the eigenvalues \( \lambda_k^{\text{data}} \) and eigenvectors (“EOFs”, \( e_k \)) of the series’ lag-covariance matrix:

\[
\lambda_k^{\text{data}} \equiv e_k^T C^{\text{data}} e_k
\]

(2)

where \( C^{\text{data}} \) is the estimated covariance of the series at lag \( |j-i| \). Figure 1 shows \( \lambda_k^{\text{data}} \) data for the 1861-1990 record of global, annual-mean, combined land and sea near-surface temperatures as compiled for the Intergovernmental Panel on Climate Change (IPCC) [Houghton et al., 1992]. Here \( M \), the rank of \( C^{\text{data}} \), is 40 sampling intervals (years), but conclusions are not sensitive to varying \( M \) from 20 to 60 years [Allen, 1992].

The \( \lambda_k^{\text{data}} \) in figure 1 are arranged in the conventional “rank-order”, i.e. by decreasing size. When SSA is used for signal detection, a symmetric/anti-symmetric pair of approximately sinusoidal EOFs, with similar, high-ranked eigenvalues, has been taken to indicate a physical oscillation. If the series contains red noise, however, then sinusoidal EOFs which are entirely due to noise may have high-ranked eigenvalues. Standard SSA applied to short realizations of AR(1) noise with the same lag-1 autocorrelation as the IPCC series (\( \gamma = 0.8 \)) indicates low-frequency oscillations in over 50% of cases, even when the EOF-selection criteria of [Vautard et al., 1992] are applied. Thus we cannot conclude that such oscillations exist on the basis of conventional SSA alone.

To resolve this problem, we introduce Monte Carlo SSA. Suppose we suspect that a series consists of a nonlinear trend contaminated with AR(1) noise. We generate an ensemble of “surrogate” series [Smith, 1992; Theiler et al., 1992], each consisting of the observed 40-year variability (reconstructed from EOFs 1 & 2 following [Ghil & Vautard, 1991]) plus a segment of AR(1) noise, generated using (1). The coefficients \( \alpha \) and \( \gamma \) are chosen to give the surrogates the same expected variance and lag-1 autocorrelation as the original data: the best-fit \( \gamma = 0.6 \), giving a decay-time \( \tau \) of \( \sim 2 \) years. We calculate lag-covariance matrices, \( C^{\text{sur}} \), for each of the surrogates and project them onto the EOFs of \( C^{\text{data}} \). The power in the \( k^{\text{th}} \) EOF is defined as \( \lambda_k^{\text{sur}} \equiv e_k^T C^{\text{sur}} e_k \); see (2). Vertical bars in figure 1 show the 95% and 80% limits of the \( \lambda_k^{\text{sur}} \) distributions.

If the \( k^{\text{th}} \) data eigenvalue, \( \lambda_k^{\text{data}} \), lies above the 95% limit of the corresponding \( \lambda_k^{\text{sur}} \) distribution, this would indicate that we can reject the null hypothesis “power associated with EOF-\( k \) is attributable to the observed
Origins of possible signals identified

Signals which cannot be distinguished from AR(1) noise in the global mean temperatures alone may nonetheless have a genuine physical origin. To investigate possible oceanic origins, we used "regression-maps" [Lim & Wallace, 1991] to identify sea surface temperature (SST) patterns associated with the different modes of the global temperatures, as follows. SSA allows the components of a time-series which contribute to variability on different time-scales to be reconstructed independently. Figure 3a of [Ghil & Vautard, 1991] shows "reconstructed components" (RCs) of global temperatures corresponding to the >40-year trend, 3-5-year, 10-year and 27-year modes. We shall refer to these as x1t to x4t respectively.

We applied the following regression model to local time series of annual-mean SSTs on a global 5° x 5° grid [Bottomley et al., 1990]:

\[ y_t = b_0 + \sum_{m=1}^{4} b_m x_{mt} + u_t \]  

(3)

where \( y_t \) is the local SST and \( u_t \) is a red noise process defined as in (1) above. The 4 RCs of the global series, \( x_{mt} \) = 1, 4, were common to all points: the "reference time series" of the regression map. At each grid point, we estimated \( b_0 \) and the coefficients \( b_m \) using the method of generalized linear regression (GLR) with missing data [Kmenta, 1981; Allen, 1992]. Because residuals are autocorrelated, using standard linear regression – replacing \( u_t \) with \( x_t \) in (3) – would result in serious underestimation of the errors, \( \sigma(b_m) \) [Davis & Vinter, 1985]. In many regions, coverage is poor prior to c. 1950. Rather than requiring any "gap-filling", we make use only of the data available: an advantage over analyses based on spatial EOFs [Folland et al., 1991].
Optimizing $\gamma$, the lag-1 autocorrelation of $u_t$, for each grid-point individually gave a global average of 0.3, implying a decay-time $T<1$ year. Thus introducing land and ice data and/or taking a global average temperature appears to increase the level of autocorrelation (as suggested by M. Ghil). Individual estimates of $\gamma$ are not very robust, so we imposed a global value of 0.3: the following results are not sensitive to varying $\gamma$, nor to omitting the (doubtful) 27-year mode.

Figures 2.1 to 2.4 show maps of regression coefficients, $b_m$. If $2 < b_m < 4$ in a particular square (medium-dark grey), then SST$_t$, $y_t$, at that point have varied in phase with, and with 2–4 times the amplitude of, the $m^{th}$ RC of the global temperatures, $x_{mt}$. Points where $|b_m| > 2\sigma(b_m)$ -- locally significant at $>95\%$ -- are enclosed by squares. A significant relationship between $y_t$ and $x_{mt}$ confined to a particular region with $b_m > 1$ would indicate that the $m^{th}$ RC of the global temperatures originates in that region.

Regression coefficients on the trend (figure 2.1) indicate a fairly uniform “warming” ($b_1 \sim 1$) over the Atlantic and Indian Oceans, with enhanced warming in the north-west Pacific. Negative coefficients (light grey squares) occur off southern Greenland and in the data-sparse Arctic and tropical Pacific, but few of these are significant, so they may simply be due to inadequate coverage in these regions.

The clearest feature related to the oscillatory components of global temperatures is the El Niño signal associated with the subdecadal RC, $x_{2t}$ (figure 2.2). The global nature of El Niño is clearly visible.

The key significant feature in the pattern associated with the 10-year RC, $x_{3t}$ (figure 2.3), is a patch of positive coefficients in the northern equatorial Atlantic, with negative coefficients south of the equator. Such a pattern of SST anomalies has been associated with variations in Sahel rainfall [Folland et al., 1991] and U.S. hurricane landfall frequency: figure 9 of [Gray, 1990].

A second patch of significant coefficients is observed in the south-east Pacific, but coverage is very poor in that region. Assessing the overall significance of such features is difficult, since we expect $\sim 5\%$ of the grid-point regressions to appear significant by chance. The 10-year pattern in the equatorial Atlantic is, however, fairly robust: it is largely unchanged if (following [Elsmere & Tsonis, 1991]) we repeat the analysis using only the years 1861–1970, 1881–1990 and 1910–1990.

Applying Monte Carlo SSA to the area-mean SST in the north equatorial Atlantic (figure 3), we found (in addition to $>40$-year variability and an ENSO signal) a 10-year period oscillation with a peak to peak amplitude of up to $>0.4^\circ$C. The evidence for this oscillation is weak: it is only distinguishable from AR(1) noise at $95\%$ confidence in the full 130-year sample, not in either the first or the last 110-year segments. A reconstruction of this signal is, however, in phase with the 10-year component of the global series; both go through a quiescent period between 1910 and 1955 during which they both undergo a $\sim 180^\circ$ change of phase. The correspondence of phase and amplitude suggests this is the origin of the 10-year mode in the global temperatures, although in the early part of the series the appearance of this mode in the global record could be due to inadequate coverage of regions outside the Atlantic. No significant 10-year oscillation could be identified in an area-mean series from the south equatorial Atlantic (confirming
Figure 3. SST anomalies in the northern equatorial Atlantic (area-mean 70W–10E, 0–20N; ~80% spatial coverage since 1880). 10-year oscillatory component (solid line) is significant against AR(1) noise at 95%. Note correspondence of phase and amplitude with 10-year signal in figure 3a of [Ghil & Vautard, 1991].

[Houghton & Tourre, 1992] that this is not a simple north-south dipole, nor from the SE Pacific.

Figure 2.4 shows no such clear “origin” of the 27-year RC. Significant coefficients occur in the Indian Ocean ($b_4>0$) and in the northwest Pacific ($b_4<0$). Time series of area-means from these regions do not, however, indicate significant interdecadal oscillations. Significant positive coefficients also occur in the eastern Pacific, but the similarity of the patterns in figures 2.2 and 2.4 in this region suggests this is a consequence of data-sparcity and amplitude-modulation of the El Niño signal. This conclusion is supported by repeating the analysis on the years 1861-1970: the 27-year pattern in the Pacific then completely disappears.

Conclusions

In our analysis of the global temperature record, the only component of variability which we were able to distinguish, at 95% confidence, from a simple form of red noise was the warming trend. Generalized regression analysis between the reconstructed trend and gridded SSTs indicated it is spatially ubiquitous, which is consistent with (although it does not, of course, establish) a global change in external forcing. We also identified subdecadal variability associated with El Niño and a possible 10-year period oscillation which appears to originate in the northern equatorial Atlantic. No evidence was found for oscillations on 20–30 year time scales, although this may simply indicate that this series of 130 years is just too short for such oscillations to be distinguished from red noise.

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References


M. R. Allen, Clarendon Laboratory, Parks Road, Oxford OX1 3PU, UK (atmmra@vax.ox.ac.uk)

L. A. Smith, Mathematical Institute, 24-29 St. Giles, Oxford OX1 3LB, UK (lenny@maths.oxford.ac.uk)

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