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Time scales and trends in the Central England Temperature data (1659-1990): A wavelet analysis

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Abstract. We have applied the standard wavelet and the adaptive wavelet transform algorithms to the record of the Central England Temperature (CET) from 1659-1990. Peaks in the CET spectra include 7.5±1.0 yr, 14.4±1.0 yr, 23.5±2.0 yr, as well as a previously unreported variation at 102±15 yr. Our wavelet analysis of CET agrees with previous results from Singular Spectrum Analysis (SSA) by *Plaut et al.* [1995] and gives additional results of variability on longer timescales. The interdecadal and century-scale variability in CET is strongly dependent on the interval of analysis. Estimates of a data trend are also shown to be sensitive to the cutoff timescale of the filter. A cooling of $\approx 0.3^{\circ}$C during 1659-1720 is found relative to the temperatures during the 1800s. The complex time dependence of the actual data cautions against using model-derived representations of natural variability on such long timescales.

Introduction

Knowledge of natural climatic variations on interannual, interdecadal and century scales is essential to the search for a human-induced effect on the global climate. Natural variations have been studied in both models and measurements. Model-derived estimates of natural variability on those low-frequency scales have been unsuitable for detecting an expected anthropogenic climate signal [e.g., *Barnett et al.,* 1996]. As for measurements, the difficulties in both detecting features and estimating the continuum level at low frequencies in power spectra of regional climatic records (both instrumental and proxy reconstructions) from which global variations are inferred have been discussed by *Mann et al.* [1995].

Plaut et al. [1995], using the SSA technique, reported the detection of 5.2, 7.7, 14.2 and 25.0 yr periods in the 335 yr CET. However, the identification of spectral features by the SSA technique is controversial [see e.g., exchanges of *Ghil and Vautard,* 1991; *Elsner and Tsonis,* 1991; *Allen et al.,* 1992 concerning the detection of the bidecadal period in the global temperature record; and *Elsner and Tsonis,* 1994; *Schlesinger and Ramankutty,* 1994 for the identification of the 65-70 yr period]. Problems may stem from, e.g., handling trends in data and quasi-periodicities in many climatic processes.

The difficulties inherent in a particular method of signal detection led us to re-examine the spectra of CET using an independent technique, the wavelet transform, which is efficient on multiple timescales. (Other methods, e.g., the Fourier transform and Maximum Entropy Method, have also been applied to CET; see *Hameed and Wyant,* 1982 and references therein.) The annual CET record is from *Manley* [1974], with updates from Vincent Macaulay [personal communication, 1994]. The CET record has value as one of the longest instrumental temperature records, although it is limited in spatial extent. We therefore limit our discussion to several technical issues of signal processing. We also do not claim to resolve all the indicated problems with traditional methods of spectral analysis but merely wish to illustrate the complementary nature of the adaptive wavelet transform in this application.

The two issues we discuss are: (1) to better quantify the variability of the low frequencies in CET, with emphasis on timescales longer than a few decades; (2) to determine trends in CET, especially their dependence on the choice of the limiting frequency of the filter.

Wavelets — Time-scale analysis of nonperiodic signals

Fourier analysis fails when a signal is not strictly periodic and when the scale properties are time-dependent. In such cases, the wavelet transform is useful [see e.g., *Holschneider,* 1995]. Applications of the wavelet transform technique to analyses of geophysical time series have been wide ranging [e.g., *Bolton et al.,* 1995; *Chao and Naito,* 1995; *Lau and Weng,* 1995].

The wavelet transform of the time series $f(t)$ is $w(a,t) = a^{-1}\int\psi\left(\frac{t'-t}{a}\right)f(t')dt'$, where a is a scaling parameter and $\psi(t)$ is the analyzing wavelet. A formula for reconstructing the function f from w can be obtained from the inverse wavelet transform. Wavelets are used for the detection of localized structures or for analysis of spectral properties. In the latter case one defines the wavelet spectrum, $M(a) = T^{-1}\int|w(a,t)|^2dt$, where T

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is the length of observational interval. We chose the normalization factor a^{-1} so that variations with the same amplitude at different timescales would contribute equally to $M(a)$.

We use here the Morlet wavelet $\psi^{\mathrm{M}}(t) = e^{-t^2/2}e^{2\pi i t}$ and the Mexican hat wavelet $\psi^{\mathrm{H}}(t) = (1 - 16t^2)e^{-8t^2}$. The Morlet wavelet has better spectral resolution while the Mexican hat has better temporal resolution. Correspondingly, we use the Morlet wavelet for spectral studies and the Mexican hat for filtering trends in real time domain. Trends are considered to be the difference between the initial data and its wavelet reconstruction.

To be a wavelet, $\psi(t)$ must have a zero mean (the admissibility condition). This condition breaks down when part of the wavelet goes beyond the interval covered by observations. The estimation of power at low frequencies in a spectrum becomes difficult when the corrupted part is comparable to the total length of data series. In a standard wavelet analysis, the corrupted parts of wavelet coefficients are simply excluded.

We introduced an adaptive wavelet transform algorithm suitable for the analysis of short time series [*Frick et al.*, 1997a; see also *Foster,* 1996 for an independent development]. The idea is to correct the wavelet for every given scale and position in such a way as to provide the admissibility condition on the real domain covered by observation. We also consider the extended version of this technique [*P. Frick, A. Grossmann and P. Tchamitchian,* manuscript in preparation, 1997], which preserves not only the zero mean value of the wavelet $\langle\psi\rangle$ but also the zero value of its first moment $\langle\psi t\rangle$.

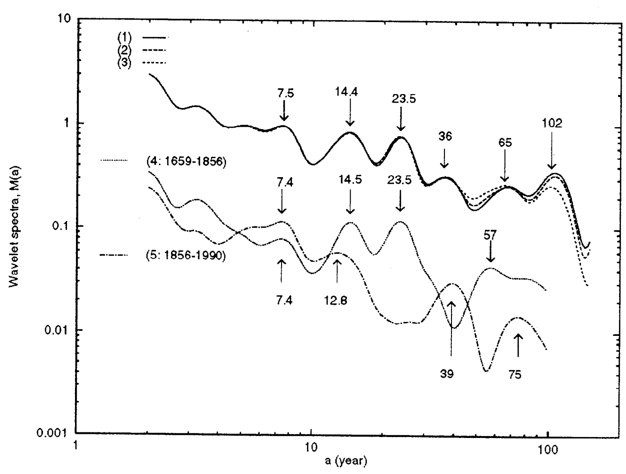

Figure 1. Wavelet spectra $M(a)$ (in units of $^\circ C^2$) of CET data (1659-1990) calculated using the Morlet wavelet with 3 different algorithms: (1) standard algorithm (S); (2,3) adaptive technique of the zero (A0) and first (A1) orders. Also shown are the wavelet spectra for the intervals (4) 1659-1856 only and (5) 1856-1990 only of CET data, calculated by using the A1 algorithm. Spectra for the full data (1659-1990) have been arbitrarily shifted vertically (for presentation) by an order of magnitude relative to the two spectra computed for the shorter intervals.

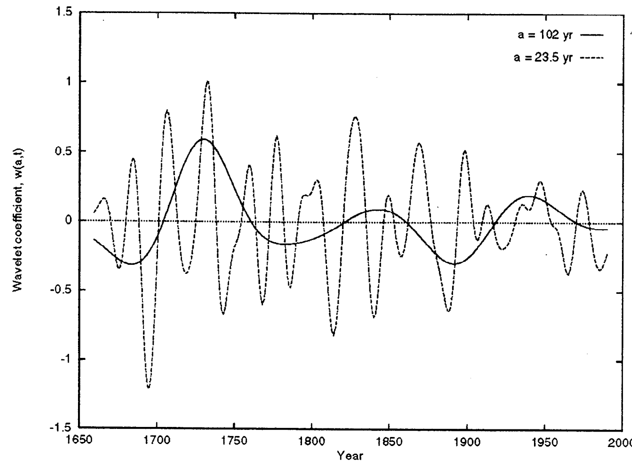

Figure 2. Variations of the wavelet coefficients (based on results from the Mexican hat wavelet), $w(a,t)$ (in units of $^\circ$C) for values of a corresponding to the peaks at 102 yr and 23.5 yr in the spectrum of CET from 1659 to 1990.

These two algorithms are called adaptive wavelets of the zero (A0) and first (A1) orders. Such a modification is useful for extracting trends from the data.

Results and Discussion

Wavelet spectra for the yearly mean CET data (1659-1990) are shown in Figure 1. Three versions of wavelet algorithms were used to obtain the spectra: the standard Morlet wavelet transform (S), and the adaptive wavelet transforms of the zero (A0) and first (A1) orders. We conclude from Figure 1 that the wavelet spectrum for the CET data is relatively stable for any of the applied wavelet algorithms. We use the results from the A1 algorithm because they give a more correct period identification for signals with trends in the data [*P. Frick, A. Grossmann and P. Tchamitchian,* manuscript in preparation, 1997].

We have also computed wavelet spectra based on the monthly data (not shown). The main finding is that despite the dominance of annual cycles in the data (i.e., the power is at least 2 orders of magnitude larger than for other scales), the resulting spectral characteristics for time scales larger than a few years remain as stable as those computed from the yearly data. This result affirms that the wavelet spectrum of yearly mean data is not simply an artifact of averaging.

The computed CET A1 wavelet spectrum scales roughly as a power law with $M(a) \propto a^{-0.6}$ at timescales between 2 and 105 yr. Beyond the peak near 102 yr, the power drops. (Note that according to our definition of the wavelet transform the spectrum scales with frequency $\omega (= 1/a)$ as $\omega^{+0.6}$. This corresponds to a power law in the traditional Fourier spectrum of $\omega^{-0.4}$ [e.g., *Frick et al.*, 1997a].) Dominant variations which we identified above this background are: 7.5±1.0 yr, 14.4±1.0 yr, 23.5±2.0 yr, 102±15 yr as well as weaker peaks at

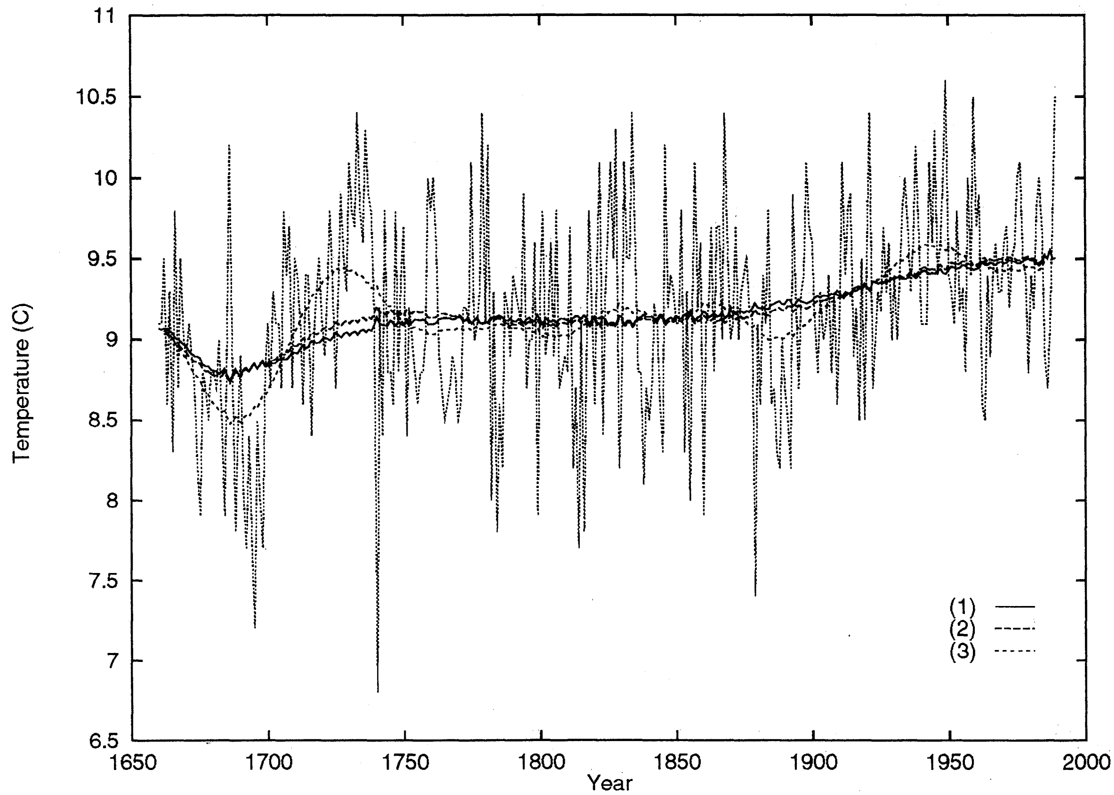

Figure 3. The yearly mean CET and the trend calculated as the difference between the observed data and wavelet reconstruction (based on results adopting Mexican hat wavelet) using the range of time scale between 2 $\leq a \leq a_{max}$ with a_{max} = 200 yr (1), 120 yr (2), and 40 yr (3).

36±8 yr and 65±15 yr (Figure 1). The *uncertainty* (i.e., resolution) of identified spectral features is given by the full-width half-maximum of each peak. Our wavelet results for the first three peaks listed are consistent with the SSA results [*Plaut et al.,* 1995]. Formal statistical significance in the *identification* (i.e., reality) of peaks for non-stationary processes is difficult to calculate in the context of the wavelet method [see e.g., *Lau and Weng,* 1995; *Foster,* 1996]. It seems, at first that the reality of the peaks can be tested at each scale by constructing an ensemble of artificial data (which is similar in structure to the measurements) drawn from a specified statistical distribution, like a Gaussian distribution. But the results may be misleading because the mean and variance for non-stationary processes are not well defined.

In connection with the 102-yr CET feature, *Frick et al.* [1997b] found a peak near 100 yr in wavelet spectra of the solar activity record recently refined by *Hoyt et al.* [1994]. Further physical understanding is needed before this coincidence can be explained.

Are the features in the wavelet spectra periodic or nearly-periodic? To test those possibilities, we computed the wavelet spectra in 1659-1856 and 1856-1990 (Figure 1, curves 4 and 5). We split the record in order to minimize the possible influence of anthropogenic greenhouse gases in the early interval. The spectra are strongly time dependent. Only the peak at 7.5-yr (and to some extent the 14.4-yr peak) is stable between the two intervals. Peaks at 23.5-yr, 36-yr, and 65-yr dominate only in one or the other of the shorter intervals, thus showing that the features are not periodic.

Figure 2 shows the temporal variation of two dominant spectral components, 23.5 yr [i.e., $w(23.5, t)$] and 102 yr [i.e., $w(102, t)$]. These components are *not* strictly periodic; they are strongly amplitude and phase modulated. For example, the amplitude of the 102-yr variation was larger before 1800 than after, and the amplitude of the 23.5-yr variation decreased after 1900.

Figure 3 shows the reconstructed long-term trend in CET (1659-1990) obtained by selectively filtering oscillations at scales between 2 yr and 40-, 120- or 200-yr. The trend estimated from the filter cutoff at 40-yr (curve 3 in Figure 3) is very similar to that of *Plaut et al.* [1995]. However, the results in Figure 3 show that the trend estimate is very sensitive to the change in cutoff from 40 yr to 120 yr. *Plaut et al.* [1995] did not consider the low frequencies at $40 \lesssim a \lesssim 200$ yr to be independent of the trend in their SSA analysis.

The low temperatures during 1659-1720 are stable against the choice of filter, which suggests that the cool interval is real. The low temperatures are coincident with the well-known Maunder minimum of solar magnetic activity and appears to be $\approx 0.3^\circ$C cooler than during the 1800s. The possible connection between the low temperatures and solar activity during the Maunder

Minimum is obvious. But a confirmation of a hypothesis of solar-caused variability remains to be proven since solar-induced mechanisms of climate change are still difficult to verify.

Another result is that most of the increased temperature in modern times began early, before circa 1860. This warming trend began before the significant increases in the emission of the anthropogenic greenhouse gases. However, it is difficult to attribute climatic cause and effect based on temperatures from a single record. If this trend can be confirmed in other records, then the variability would have to be explained.

Note added in review: A recent SSA analysis of 27 proxy records of temperature, with durations ranging 173 to 1481 years, by *Mahasenan et al.* [1997], appears to confirm the relatively cool temperature during 1659-1720 found in CET (e.g., see the northern hemisphere records in their Figures 1, 2 and 3). *Mahasenan et al.* [1997] found a significant, at a $\sim 80\%$ confidence level against a null-hypothesis of AR(1) noise, oscillation on a timescale of ~ 80 years in annual temperature record of Central Europe (1550-1979), but did not find any periods > 80 years (based on their confidence level) in CET over 1730-1987. These results are not inconsistent with our findings concerning the non-stationarity of the decadal, inter-decadal, and century-scale oscillations in CET.

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