JOURNAL OF GEOPHYSICAL RESEARCH, VOL. ???, XXXX, DOI:10.1029/,

Submitted

Comment on "Influence of the Southern Oscillation on tropospheric temperature" by J. D. McLean, C. R. de Freitas, and R. M. Carter

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Abstract. *McLean et al.* [2009] claim that the El Niño/Southern Oscillation (ENSO), as represented by the Southern Oscillation Index (SOI), accounts for as much as 72% of the global tropospheric temperature anomaly (GTTA) and an even higher 81% of this anomaly in the tropics. They conclude that the SOI is a "dominant and consistent influence on mean global temperatures," "and perhaps recent trends in global temperatures". However, their analysis is incorrect in a number of ways, and greatly overstates the influence of ENSO on the climate system. This comment first briefly reviews what is understood about the influence of ENSO on global temperatures, then goes on to show that the analysis of MFC09 severely overestimates the correlation between temperature anomalies and the SOI by inflating the power in the 2–6 year time window while filtering out variability on longer and shorter time scales. It is only because of this faulty analysis that they are able to claim such extremely high correlations. The suggestion in their conclusions that ENSO may be a major contributor to recent trends in global temperature is not supported by their analysis or any physical theory presented in that paper, especially as the analysis method itself eliminates the influence of trends on the purported correlations.

1. Introduction

McLean et al. [2009] (henceforth MFC09) have recently argued that most of the decadal and longer-term variation in large-scale tropospheric temperatures can be explained by a single factor–the El Niño/Southern Oscillation (ENSO). They argued that more than two thirds of the interseasonal and longer-term variability in global tropospheric temperature anomaly (GTTA) (72% using the 29-year-long MSU satellite record and 68% using the longer 50-year RATPAC-A record), and an even larger 81% of the variation in tropical (20°S-20°N) tropospheric temperatures, can be explained by the long-term variations in the Southern Oscillation Index (SOI).

Unfortunately, their conclusions are seriously in error because their analysis is based on inappropriate application of filters to the data used. It is well established that ENSO accounts for much of the interannual variability in tropospheric temperatures (*Trenberth et al.* [2002] and references therein). By filtering they have reduced the time series studied to a narrow frequency band, thereby exagerrating what is already well-known.

Consequently, their estimates are at marked variance with essentially every other study of the connection between ENSO and large-scale temperature variability, particularly with regard to the role of ENSO in any long-term warming trends, that has been carried out over the past two decades. *Jones* [1989] found that roughly 30% of the variation in global annual mean surface temperature could be explained by the SOI over the period 1867-1988 (with the SOI leading temperatures by 6 months). *Wigley* [2000] found that the lower tropospheric warming trend over the 21 year period 1979-1999 increases from 0.15°C/decade to 0.25°C/decade after the joint impacts of ENSO and volcanic aerosols are accounted for and removed. A related analysis by *Santer et al.* [2001] found trends of 0.210 to 0.25°C/decade at the surface to 0.056 to 0.158°C/decade in the lower troposphere, after the joint removal of both factors. Using Niño 3.4 region (170°-120°W, 5°N-5°S) sea surface temperature (SST) anomalies as an index of ENSO, *Trenberth et al.* [2002] found a residual global mean surface temperature trend of 0.4°C over the period 1977-1998 after ENSO impacts alone are removed. More recently, *Thompson et al.* [2008] removed an estimate of global temperature variations associated with both ENSO and the so-called cold ocean/warm land or "COWL" pattern of extratropical temperature variation, and found a residual global mean surface warming of 0.4°C over the 1950-2006 period.

In all of these previous analyses, ENSO has been found to describe between 15 and 30% of the interseasonal and longer-term variability in surface and/or lower tropospheric temperature, but little of the global mean warming trend of the past half century. Here, we explain how MFC09 results come about from (a) inappropriate statistical averaging and differencing procedures which distort the frequency-domain characteristics of the time series analyzed, effectively removing long-term trends, and (b) inappropriate splicing of different data products. We identify some additional problems in their interpretation of their analyses.

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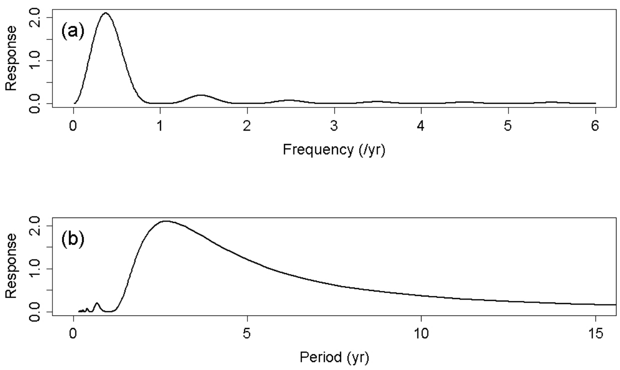

Figure 1. Frequency response due to the filter used by MFC09, (a) as a function of frequency and (b) as a function of period.

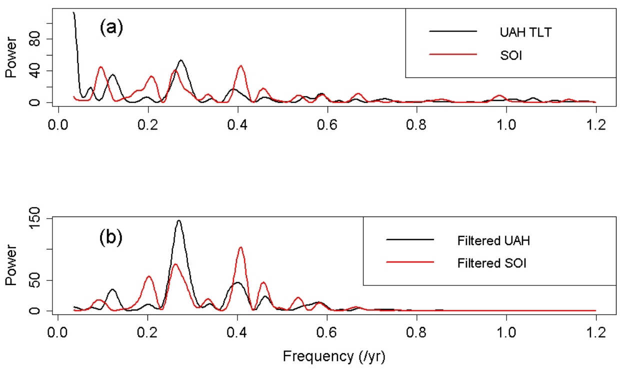

Figure 2. Fourier spectra for the UAH and SOI time series from Dec. 1979 to the present, both (a) before filtering and (b) after filtering.

2. Method of MFC09

For all monthly time series (the global and tropical MSU temperature estimates from UAH and the SOI from the Australian Government Bureau of Meteorology), the analysis of MFC09 first takes 12-month moving averages of the data, then takes differences between those values which are 12 months apart. The first step filters the high-frequency variation from the time series, while the second step filters low-frequency variation. The latter step is perhaps the most problematic aspect of their analysis. It approximates taking the time derivative of the smoothed series, and therefore any linear trend which may be present in the original data will be reduced to an additive constant. Since additive constants have no effect on the correlation between time series, any subsequent correlation-based analysis of the processed time series can tell us absolutely nothing about the presence or causes of trends in the original data.

In more detail, the combined processing acts effectively as a bandpass filter. An input signal consisting of a pure sinusoid at frequency ν cycles per year, given by $x(t) = \sin(2\pi\nu t)$ (with t in years), sampled monthly and subjected to the filter used by MFC09, will produce an output signal with frequency-dependent amplitude

$$A(\nu) = \frac{\sin^2(\pi\nu)}{6\sin(\frac{1}{12}\pi\nu)}. \tag{1}$$

The variance due to such a signal will, like its power in a Fourier spectrum, be proportional to the square of that factor. Hence the variation of any signal will be bandpass-filtered, by the proportions plotted in Figure 1. A comparison of the Fourier power spectra for the UAH and SOI time series from Dec. 1979 to the present, before and after filtering, computed using the date-compensated discrete Fourier transform [*Ferraz-Mello*, 1981], clearly shows the removal of power at both low and high frequencies, exactly where the disagreement between the spectra of these time series is greatest (Figure 2).

Although the filtering dramatically alters the power spectrum of the UAH time series, its effect at low frequencies is even more drastic when applied to the RATPAC-A data. This is because the RATPAC-A data exhibit larger secular change over the observed time span, showing a larger trend and covering a longer time span. This amplifies the effect of the filter on the variation, as is evident from a comparison of the Fourier spectra for RATPAC-A data (global) before and after filtering (Figure 3). The extremely high spectral

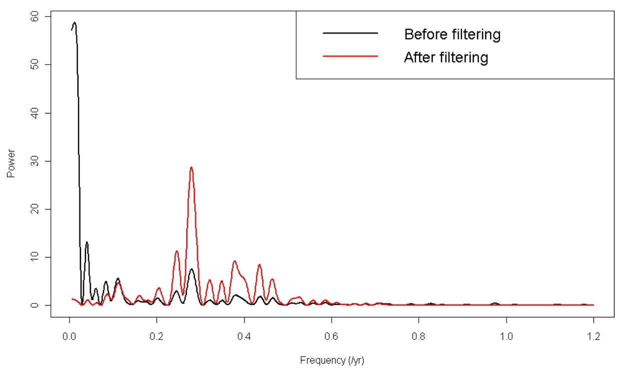

Figure 3. Fourier spectra for the RATPAC-A global time series, before filtering (black) and after (red).

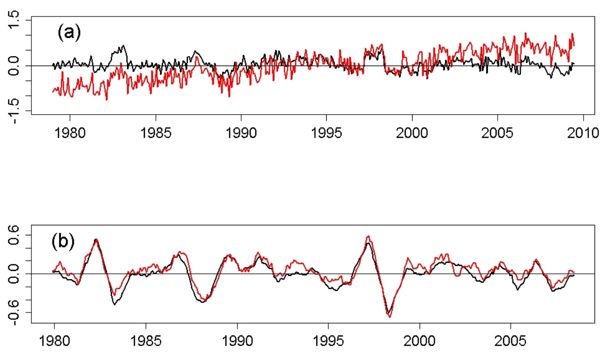

Figure 4. (a): Artificial data proportional to the SOI (black), and with normally-distributed white noise and a linear trend added (red). (b): Filtered versions (using the MFC09 procedure) of the series in (a).

power at very low frequencies, which is the dominant feature of the spectrum due to the larger trend and longer duration of the RATPAC-A data series, is entirely eliminated by the filtering.

3. Justification for the Filter

MFC09 note that even after initially taking the 12-month moving average the correlation between the SOI and GTTA remains poor, saying "*A 5-month lag produced the best match of key turning points but the overall correlation of -0.223 is quite weak. This weak correlation may be due to the period during which volcanic eruptions exert an influence on temperature, or to noise caused by short-term forces such as wind, within the two data signals, both of which are given as monthly averages, from which these 12-month running averages were calculated.*"

They then suggest that the derivative filter is applied for the specific purpose of removing the noise: "*To remove the noise, the absolute values were replaced with derivative values based on variations. Here the derivative is the 12-month running average subtracted from the same average for data 12 months later.*"

However, taking the derivative of a time series does not remove, or even reduce, short-term noise. It has the *opposite* effect, *amplifying* the noise while attenuating the longer-term changes. Thus, the use of the differencing filter has not been justified, as it has precisely the opposite effect to that invoked by the authors. The noise due to short-term "forces" has *already* been reduced by the moving-average step. Yet even this noise should not have been removed if the authors truly wish to estimate how much of the total variation in GTTA is due to variations in the SOI.

4. Demonstration of the MFC09 Filter

As an illustration, we constructed an artificial "temperature" time series as -0.02 times the SOI time series from Dec. 1979 to the present, $x(t) = -0.02 \times SOI(t)$. Of course the correlation between x and the SOI here is precisely -1, and for this artificial variable the SOI accounts for 100% of the variation. We then added normally-distributed white noise and a linear trend to generate a new series $y(t) = x(t) + N(0, \sigma) + a(t - 1995)$ with $\sigma = 0.2$ and $a = 0.05$. The original and modified series are shown in Figure 4 (top panel).

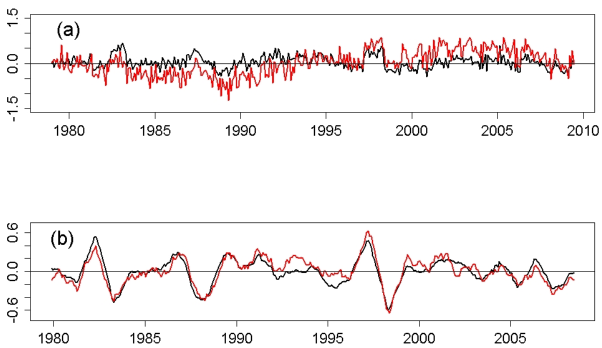

Figure 5. (a): Artificial data proportional to the SOI (black), and with normally-distributed white noise and a sinusoidal signal added (red). (b): Filtered versions (using the MFC09 procedure) of the series in (a).

The squared correlation between the modified series and the SOI series is only $R^2 = 0.0171$. When both are transformed with the filter used by MFC09 (Figure 4 bottom panel) the squared correlation between the filtered series is $R^2 = 0.8295$. However, it would be grossly misleading to claim that variations in the SOI account for 83% of the variation in the artificial series; in fact the SOI accounts for less than 2% of the variance.

Such hugely inflated correlations do not hold just for the addition of a linear trend, but hold more generally for any low-frequency variability. We also took the artificial signal proportional to the SOI and added the same noise and a sinusoidal signal with a period of 30 years, defining $z = x + N(0, \sigma) + 0.5 \sin(2\pi(t - 1995)/30)$ (Figure 5 top panel). Now the squared correlation between the SOI and the artificial signal z is $R^2 = 0.1928$. But after the filtering of MFC09 (Figure 5 bottom panel) the squared correlation rises to $R^2 = 0.8821$. Again, it is certainly not correct to claim that variations in the SOI account for 88% of the variation of the artificial data, when in fact they acount for only 19%.

In spite of the extreme distorting effect of their filter, MFC09 consistently refer to the correlations and fractions of explained variation they derive as between the SOI and tropospheric temperature, both in the abstract and the conclusions. They make no attempt to draw attention to the fact, let alone emphasize, that the reported correlations are between heavily filtered time series, or between estimated derivatives of time series. This failure causes what is essentially a mistaken result to be misinterpreted as a direct relationship between important climate variables.

MFC09 further claim that the statistical properties of the time series for the SOI and GTTA, in which the two halves of a time series have different means but similar variability about that mean, are indicative of "a stepwise shift in the base values of each factor". However, this is not the case. For any time series consisting of a linear trend plus noise, say $x(t) = at + \epsilon(t)$ over the interval $-T \leq t \leq T$, where $\epsilon(t)$ is any noise function with zero mean, variance s^2 and time scale substantially shorter than T, the expected means over the first and second halves of this interval are of course $-aT/2$ and $aT/2$ respectively but the expected variance of each half about these values will be equal at $a^2T^2/12 + s^2$. Thus, their analysis here in no way supports their claim of a step change.

5. Trend in GTTA

In Figure 7 of MFC09, the authors plot actual GTTA (not filtered versions) against the SOI (using different axes) to illustrate the quality of the match between them. However the GTTA signal they plot is a splice of RATPAC-A data through 1979 followed by UAH TLT data since 1980. RATPAC-A data show a pronounced trend over the entire time span, which is visually evident from Figure 4 in MFC09, the temperature line rising away from the SOI line. It is especially misleading simply to append one data set to the other because there is a zero-point difference between the two. The mean values of RATPAC-A and UAH TLT data during their period of overlap differ by nearly 0.2 K, so splicing them together without compensating for this introduces an artificial 0.2-degree temperature drop at the boundary between the two. Unfortunately this is obscured by the fact that the graph is split into different panels precisely at the splicing boundary.

In any case, the filter used in MFC09 does more than remove linear trends. As we have shown, it strongly attenuates all low-frequency signal components and greatly exaggerates the correlation between tropospheric temperature and the SOI.

6. Conclusion

It has been well known for many years that ENSO is associated with significant variability in global mean temperatures on interannual timescales. However, this relationship (which, contrary to the claim of MFC09, **is** simulated by global climate models, e.g. *Santer et al.* [2001]) cannot explain temperature trends on decadal and longer time scales. The analysis of MFC09 grossly overstates the influence of ENSO, primarily by filtering out any signal on decadal and longer time scales. Their method of analysis is *a priori* incapable of addressing the question of causes of long-term climate change. In fact, the general rise in temperatures over the 2nd half of the 20th century is very likely predominantly due to anthropogenic emissions of greenhouse gases [*IPCC*, 2007].

Acknowledgments. This work was supported by the Global Environment Research Fund (S-5-1) of the Ministry of the Environment, Japan. NCAR is supported by the National Science Foundation. PDJ has been supported by the US Dept. Of Energy (grant DE-FG02-98ER62601).

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