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Empirical analysis of the solar contribution to global mean air surface temperature change

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ABSTRACT

The solar contribution to global mean air surface temperature change is analyzed by using an empirical bi-scale climate model characterized by both fast and slow characteristic time responses to solar forcing: $\tau_1 = 0.4 \pm 0.1$ yr and $\tau_2 = 8 \pm 2$ yr or $\tau_2 = 12 \pm 3$ yr. Since 1980 the solar contribution to climate change is uncertain because of the severe uncertainty of the total solar irradiance satellite composites. The sun may have caused from a slight cooling, if PMOD TSI composite is used, to a significant warming (up to 65% of the total observed warming) if ACRIM, or other TSI composites are used. The model is calibrated only on the empirical 11-year solar cycle signature on the instrumental global surface temperature since 1980. The model reconstructs the major temperature patterns covering 400 years of solar induced temperature changes, as shown in recent paleoclimate global temperature records.

1. Introduction

Estimating the solar contribution to global mean air surface temperature change is fundamental for evaluating the anthropogenic contribution to climate change. This is regarded as one of the most important issues of our time. While some theoretical climate model studies (Hegerl et al., 2007; Hansen et al., 2007; IPCC, 2007) indicate that the solar variability has little effect on climate (these studies estimate that less than 10% of the global warming observed since 1900 is due to the sun), several empirical studies suggest that large climatic variations are well synchronized with solar variations and, therefore, climate is quite sensitive to solar changes (Eddy, 1976; Hoyt and Schatten, 1997; White et al., 1997; van Loon and Labitzke, 2000; Douglass and Clader, 2002; Kirkby, 2007, Scafetta and West, 2005, 2006a, 2006b, 2007, 2008, Shaviv, 2008; Eichler et al., 2009; Soon, 2009; Svensmark and Friis-Christensen, 2007).

Theoretical studies rely on climate models. Two alternative approaches are commonly used: energy balance models (EBM) (for example: Crowley et al., 2000; Foukal et al., 2004) and general circulation models (GCM) (for example, Hansen et al., 2007). These models are based on the idea that climate is forced by solar variations, volcano activity, aerosols and several greenhouse gases (CO_2, CH_4, etc.). These forcings are theoretically evaluated and used as inputs of the models. The climate sensitivities to the forcing are estimated according to the known physics. This known physics is implemented in the models. The models contain a certain number of climate mechanisms such as water vapor feedback, cloud formation, energy transfer, etc. The major problem with this approach is that the physics implemented within the models may be severely incomplete. Specifically, some key variables such as the climate sensitivity to CO_2 changes are severely uncertain.

For example, according the IPCC (2007) a doubling of CO_2 may induce a temperature increase from 1.5 to 4.5 K, and more. This large uncertainty is mostly due to the current poor understanding and modeling of water vapor and cloud formation feedbacks which can have large effects on climate (Kirkby, 2007; Shaviv, 2008). Indeed, significant discrepancies between climate model predictions and data are observed (Douglass et al., 2007; Lean and Rind, 2008), and several climate mechanisms are still poorly understood, as reported by numerous scientific papers (Idso and Singer, 2009).

An alternative approach is based on empirical multilinear regression models. It is assumed that not all physics is known or implemented in the models. The forcings are used as inputs of EBMs whose outputs are not the actual temperature signatures generated by the various forcings but waveform functions that are assumed to be proportional to such signatures. The temperature is supposed to be a linear superposition of these rescaled output waveforms and linear amplification coefficients are evaluated by means of a multilinear regression analysis of a given temperature record. Thus, it is assumed that

$$\Delta T(t) = \sum_F \alpha_F S_F(t) + N(t), \tag{1}$$

where the regression coefficients, α_F, are the linear amplification coefficient associated to a given forcing F; $S_F(t)$ is the output

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waveform generated by the chosen EBM forced with a given forcing $F(t)$; and $N(t)$ is the residual signal that is interpreted as natural climate variability. The above methodology has two major variants according to the particular EBM used to generate the waveforms.

Some authors (North et al., 2004; Hegerl et al., 2006, 2007) use typical EBMs. The adoption of EBMs is particularly useful if the interest focuses on local temperature records, but becomes less useful if the interest is in the global average temperature. In fact, when the EBM outputs need to be averaged on the entire globe an EBM does not perform too much differently from a simple low pass RC-like filter with appropriate relaxation time responses. The relaxation time response of a thermodynamic system is related to the heat capacity of the system itself. For example, I found that the EBM used by Crowley et al. (2000), where the output is averaged on the entire globe, is approximately simulated with a low-pass RC-like filter with characteristic time $\tau = 10\,\mathrm{yr}$, as deduced from the data published with Crowley's paper. In fact, some other authors (for example, Lockwood, 2008) use low-pass RC-like filters with a specific characteristic time response for each forcing.

On the contrary, other authors (Douglass and Clader, 2002; Gleisner and Thejll, 2003; Lean and Rind, 2008) do not use traditional EBMs. These authors just assume that the output waveform functions coincide with the corresponding forcing functions with some time-lag shifts. Thus, these authors use Eq. (1) with $S_F(t) = F(t - \tau_F)$.

The results of these multilinear regression model studies are quite interesting, also because they differ significantly from each other. Hegerl et al. (2007) found a large variability of the climate sensitivity to the total solar irradiance (TSI) changes depending on the paleoclimate temperature records that they used. In some cases these authors even found *negative* values of the climate sensitivity to TSI changes which is evidently not physical because it would imply that global climate cools when TSI increases and warms when TSI decreases. Probably, the significant uncertainty present in the paleoclimate temperature reconstructions and in the forcing functions is responsible for these ambiguous results. These results show that the multilinear regression analysis methodology is inefficient when applied to long and uncertain records.

Lockwood (2008) applied a nonlinear multivariate fit with several parameters on a three decades surface temperature record and found that the surface climate signature associated to the 11-year solar cycle has a peak-to-trough amplitude of about 0.05 K. On the contrary, Tung and Camp (2008) using similar data found a peak-to-trough solar signature amplitude of about 0.2 K. Douglass and Clader (2002), Gleisner and Thejll (2003), Lean and Rind (2008) and several other studies (White et al., 1997; Scafetta and West, 2005) found that the surface climate signature associated to the 11-year solar cycle has a peak-to-trough amplitude of about 0.1 K. Indeed, this 0.1 K solar cycle signature in the global surface temperature appears to be the most common result among the empirical studies (IPCC, 2007, see p. 674 for details), in particular since 1980. Herein, I will refer to it as the empirical estimate of the 11-year solar cycle signature on global surface temperature since 1980.

Indeed, it is relatively easy to find this signature. Fig. 1 shows the original global surface temperature (Brohan et al., 2006) (curve 'b'), and the volcano (curve 'c') and the ENSO (curve 'd') temperature signatures, as recently estimated by Lockwood's (2008) model. The curve 'a' in the figure shows the temperature detrended of the volcano and of the *detrended* ENSO signature components. The detrended ENSO signature component is obtained by detrending the ENSO signature of its four year moving average smooth curve, which is shown in the figure in the solid thick curve 'd'. This operation does not change the final results drastically but it is done because the ENSO signature may be capturing part of the solar decadal signature on climate, so this smooth component is put back in the data before a comparison with the solar record is studied. Also Lockwook's residual signal may still contain a solar signature: therefore, it is kept in the data to avoid an inappropriate filtering.

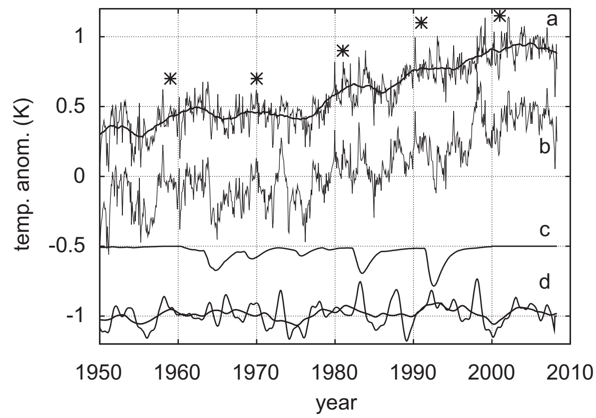

Fig. 1. Temperature components. The curve (b) is the original global surface temperature (Brohan et al., 2006). The curve (c) is the volcano signature on the temperature as estimated by Lockwood (2008). The thin curve (d) is the ENSO signature on the temperature as estimated by Lockwood (2008); the thick curve is a four year moving average of the thin curve. The thin curve (a) is the surface temperature minus the volcano and ENSO signatures plus the thick smooth curve in (d); the thick smooth curve in (a) is a four year moving average of the thin curve (a). The curves are dislocated at 0.5 K intervals for visual convenience. The '*' symbols indicate the position of the TSI maxima.

The filtered temperature signal (curve 'a' in Fig. 1) shows a clear decadal oscillation with a peak-to-trough amplitude of at least 0.1 K, which is in phase with the solar cycles. The '*' symbols in the figure indicate the position of the 11-year solar cycle maxima and, on average, there is a lag-time of about one year between the solar maxima and the maxima of the smooth curve 'a', which fits the prediction of some EBMs (see Fig. 1b in North et al., 2004).

The peak to trough empirical amplitude regarding the 11-year solar cycle signature on global surface temperature is not reproduced by traditional GCM and EBM estimates. North et al. (2004) used five different EBMs and found that the climate signature associated to the 11-year solar cycle is, on average, twice than the theoretical predictions (see their figures 1 and 4). The climate models used by Crowley et al. (2000), Foukal et al. (2004) and Hansen et al. (2007) predict an even lower solar signature on climate with a peak to trough amplitude of about 0.02–0.04 K. It is reasonable to think that current climate models are missing important climate mechanisms that amplify the solar signature on climate, also by a large factor (Shaviv, 2008). In fact, these models assume that the sun can alter climate only by means of direct TSI forcing while there are strong evidences that variation of direct UV radiation and cosmic rays, which affect cloud formation and change the albedo, can play a major role in climate change (Pap et al., 2004; Kirkby, 2007). Thus, there are both empirical and theoretical reasons to believe that traditional climate models cannot faithfully reconstruct the solar signature on climate and are significantly underestimating it.

The alternative approach that is based on multilinear regression reconstruction of climate has also some serious shortcomings. Multilinear regression analysis is very sensitive to the shape of the temperature function and to the shape of the functions used as constructors. Thus, uncertainties in the data and/or in the models used to construct the waveform components yield suspicious regression coefficients, as Hegerl et al. (2007) found. Moreover, multilinear regression analysis is based on the