Attribution of global surface warming without dynamical models

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[1] Detection and attribution studies of observed surface temperature changes have served to consolidate our understanding of the climate system and its past and future behaviour. Most recent studies analysing up-to-date observations have relied on general circulation models (GCMs) to provide estimates of the responses to various external forcings. Here we revisit a methodology which instead estimates the responses using a simple model tuned directly to the observed record, paralleling a technique currently used with GCM output. The effects of greenhouse gases, tropospheric sulphate aerosols, and volcanic aerosols are all detected in the observed record, while the effects of solar irradiance are unclear. These results provide further observational constraints on past and future warming estimates consistent with those from recent studies with GCMs, supporting the notion that current estimates are robust against the modelling system used. **Citation:** Stone, D. A., and M. R. Allen (2005), Attribution of global surface warming without dynamical models, *Geophys. Res. Lett.*, *32*, L18711, doi:10.1029/2005GL023682.

1. Introduction

[2] The detection and attribution of climate change plays a central role in climate change research, both because of its role in connecting the many other research branches in the field [*Intergovernmental Panel on Climate Change*, 2001] and because of its ultimate implications for individual stakeholders [*Allen*, 2003; *Allen and Lord*, 2004]. A decade has passed since studies comparing estimated climate responses to external forcings against the observed surface air temperature (SAT) record started to find a detectable anthropogenic contribution [*Santer et al.*, 1995; *Hegerl et al.*, 1996; *North and Stevens*, 1998]. More recent studies reinforce and elaborate upon these results [*Mitchell et al.*, 2001] (see also P. A. Stott et al., Robustness of estimates of greenhouse attribution and observationally constrained predictions of global warming, submitted to *Journal of Climate*, 2005, and D. A. Stone et al., A multi-model update on the detection and attribution of global surface warming, submitted to *Journal of Climate*, 2005) (the latter hereinafter referred to as Stone et al., submitted manuscript, 2005b).

[3] Many of these analyses require estimates of spatio-temporal response patterns from general circulation models (GCMs) and so rely on the assumption that these models are correctly reproducing the climate system. However, a variant to the standard detection and attribution procedure [*North and Kim*, 1995; *North and Wu*, 2001] (see also D. A. Stone, The detection and attribution of climate change using an ensemble of opportunity, submitted to *Journal of Climate*, 2005) (hereinafter referred to as Stone et al., submitted manuscript, 2005a) does not require GCM estimates of the response patterns. Instead, they can be estimated directly from the observed record using a simple zero dimensional climate model. Assuming such a model adequately represents the climate system at the global scale, the advantage is that the model can be objectively tuned to the observational record. This paper applies this methodology to the current observed SAT record and so provides an estimate of the detection and attribution of the response of the climate system to external forcings that is entirely independent of GCM estimates of the response. While studies using GCMs can be preferable for a number of reasons, the intention here is to investigate whether results are robust against the use of climate modelling systems of varying complexity.

2. Data and Method

[4] We analyse the data set of *Jones and Moberg* [2003] containing monthly mean SAT from station observations amalgamated onto a $5^\circ \times 5^\circ$ grid. Data from a given month and grid cell are retained provided that at least half of that year has data and at least 10 years of the base climatological period of 1961–1990 has data. Global annual means are calculated and used in the analysis.

[5] Figure 1 shows the estimates of the evolution of the four main radiative forcings over the 1891–2100 period used in this analysis. These are the forcing estimates for greenhouse gases (GHG), tropospheric sulphate aerosols (SUL), stratospheric volcanic aerosols (VOL), and solar irradiance (SOL) compiled by PCMDI for use by modelling groups for their simulations submitted for analysis to the IPCC's 4th Assessment Report. The SUL forcing is derived from the burden estimates of *Boucher and Pham* [2002] and accounts for both the direct and indirect effects, the VOL forcing follows C. M. Ammann et al. (Coupled simulations of the Twentieth Century including external forcing, submitted to *Journal of Climate*, 2005), and the SOL forcing follows *Lean et al.* [1995]. Forcing information, such as greenhouse gas concentrations, has been converted to radiative forcing estimates according to the formulae used by Stone et al. (submitted manuscript, 2005a). The forcings estimates are extended to 2100 according to the IPCC SRES A1B scenario, with VOL and SOL forcings held constant through the future; this scenario is arbitrarily chosen on account of its popularity in other studies. We do not consider uncertainties in past or future forcing scenarios in this study.

[6] We apply a methodology of detecting and attributing changes similar to that employed in a number of other studies [*Hegerl et al.*, 1996; *Jones and Hegerl*, 1998; *North*

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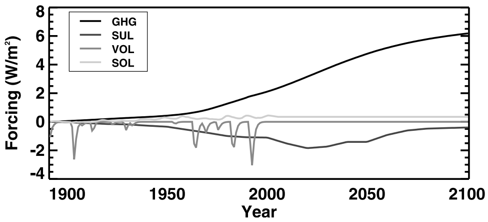

Figure 1. Characteristic global forcing time series used for the IPCC "20c3m" (historical) and "SRES A1B" (future) climate simulations covering 1891 through 2100.

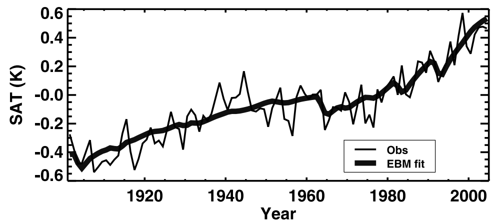

Figure 2. Plot of global annual mean SAT time series from 1901 to 2004. The combined EBM fit is shown with the thick line.

and Stevens, 1998; *North and Wu*, 2001]. The details of the variant used here are described in detail by Stone et al. (submitted manuscript, 2005a). The first step involves extracting the response signals to the individual forcings. This involves fitting a sum of n different energy balance models (EBMs) corresponding to the n forcings. These EBMs are of the form

$$c_i \frac{d\vec{T}_i}{dt} = \vec{F}_i - \lambda_i \vec{T}_i - k_i \frac{d^2\vec{T}_i}{dz^2} \tag{1}$$

where c_i is the heat capacity, $\frac{1}{\lambda_i}$ is the climate sensitivity, and k_i is the vertical diffusivity for the forcing i. The c_i, λ_i, and k_i parameters are tuned such that the total SAT response, $\vec{T} = \sum_i \vec{T}_i$, to the forcings most closely resembles the observed mean SAT time series.

[7] The estimated individual EBM responses $\vec{T}_i$ to forcing i are then used in the standard multiple regression methodology used in many detection and attribution studies [*Allen and Tett*, 1999]. Under this, we express observed temperature changes $\vec{T}_{obs}$ as a linear sum of the simulated responses determined for each forcing ($\vec{T}_i$) plus a residual ($\vec{\nu}_0$):

$$\vec{T}_{obs} = \sum_{i=1}^{n} \vec{T}_i \beta_i + \vec{\nu}_0. \tag{2}$$

The β_i's are scaling factors estimated in the regression to minimize the variance of the residual term $\vec{\nu}_0$. Estimates of the covariance of the residual term are needed both for this minimisation and for estimating the distributions of the β_i scaling parameters. We estimate the covariance of the residual term using control simulations provided by the various modelling centres around the world to the IPCC 4th Assessment Model Output database (https://esg.llnl.gov:8443/index.jsp) in the same manner as Stone et al. (submitted manuscript, 2005b). Additional uncertainty arises from the overfitting error involved in fitting a 12 parameter EBM to 104 data points; this factor is not included in our estimates of the distributions of the β_i scalings but tests by Stone et al. (submitted manuscript, 2005b) suggest that this can lead to an underestimate of up to a factor of 1.5 in the total uncertainty. While the two step nature of the analysis is not absolutely necessary in the present context, the intention is to parallel recent studies performed using GCM output.

3. Results

[8] The combined EBM fit to the observed SAT record is shown in Figure 2. Like the observed record, the EBM surrogate rises gradually over the first 40–50 years of the record, then levels off until ~1970, and finally rises more steeply over the most recent thirty years. Small but visible dips occur during the years following volcanic eruptions. The only notable discrepancy between the fit and the observed record occurs around 1940, when for about 10 years the EBM fit underestimates the observed values.

[9] The EBM parameters that provide this best fit are shown in Figure 3. Values of the heat capacity parameter correspond to mixed layer depths of about 20 m (GHG) to 110 m (SOL), with the diffusivity parameter corresponding to vertical diffusivity values ranging over approximately 5×10^{-9} m^2s^{-1} (SOL) to 5×10^{-8} m^2s^{-1} (VOL). The estimates of the parameters across forcings vary more widely than would be expected on physical grounds (for instance due to the time scale of the forcing impulse), indicating that they are poorly constrained, as noted elsewhere (Stone et al., submitted manuscript, 2005a, 2005b). Of course, the purpose of these EBMs is to provide surrogates of the actual responses to the individual forcings, so accurate parameter estimation is secondary insofar as the estimated parameter sets produce realistic output through the EBM. A relevant quantity for characterising transient climates is the transient climate response (TCR) (D. J. Frame et al., Challenging climate sensitivity, manuscript in preparation, 2005). This is the temperature change after a linear increase in forcing equal to a doubling of CO_2 at a rate of 1% per year (over 70 years). Estimates of the TCR Figure 3 are more similar across forcings than are the EBM parameters, suggesting that the TCR is better constrained than are individual EBM parameters. The lower SOL and VOL values are consistent with results when the same analysis is applied to output from GCMs (Stone et al., submitted manuscript, 2005b), although the coincidence of El Niño and volcanic events in the observational record

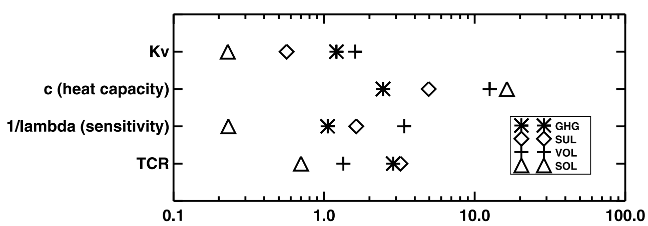

Figure 3. The EBM parameters for each of the forcings that provide the best fit to the observations; c_i, the heat capacity, is in units of $W \cdot year \cdot m^{-2} \cdot K^{-1}$; $\frac{1}{\lambda_i}$, the climate sensitivity, is in $K \cdot m^2 \cdot W^{-1}$; k_i, the vertical diffusivity, is in $W \cdot K^{-1}$; the transient climate response, TCR, is in K.

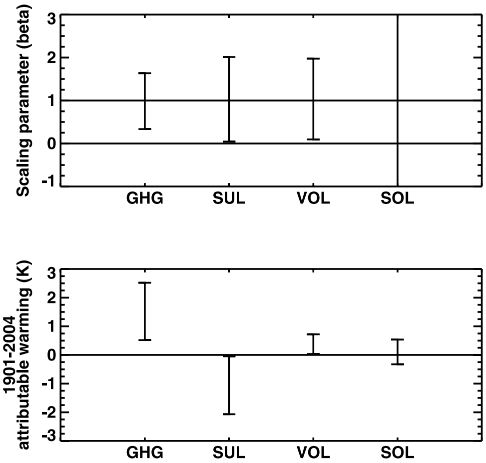

Figure 4. (top) The 90% confidence intervals of the amplitude scalings (β_i) derived from the regression of observed SAT changes onto the EBM estimates of the response patterns to each of the forcings. (bottom) The resulting 90% confidence intervals of the estimated SAT change over the 1901–2004 period attributable to each of the forcings.

could imply an underestimate of the VOL response [*Santer et al.*, 2001].

[10] With these estimates of the EBM parameters, we now have estimates for the responses of the real climate system to the separate forcings. Therefore, we can now proceed with the traditional multiple regression approach to detection and attribution using these response estimates. The resulting estimated values of the scaling parameters are shown in Figure 4. These scalings are the factors with which we must multiply the EBM temporal response patterns in order to achieve a best fit with the observed record. The estimates of the 90% confidence intervals on the scaling parameters are derived from covariance estimates from the control simulations of the GCMs and represent the only use of GCM data in this analysis. It should be remembered that these estimates of the confidence intervals do not take account of uncertainty arising from the EBM fitting step of the analysis.

[11] The effects of GHG, SUL, and VOL forcing are all detected at the 5% level because a scaling of zero, i.e. their absence, is inconsistent with the observed record. On the other hand, the effects of SOL are poorly constrained and so are not detected. The scalings for all forcings are consistent with one, i.e. our estimated responses: because our estimates of the responses are derived from the observations themselves, we expect the scalings to be near a value of one in this analysis. These results generally hold when a version of the EBM with $k_i = 0$ is used (not shown); the exception is the VOL response, which we would expect to depend more strongly on the diffusivity because of the shorter time scale of the VOL forcing.

[12] By combining our EBM estimates of the temporal response patterns and the observational constraints on their amplitude, we now have observationally constrained estimates of the contributions of the various forcings to past climate variations. This means that we can, for example, determine the degree to which the various forcings contributed to the SAT difference between 2004 and 1901 [*Allen et al.*, 2000]. These attributable warmings are shown in Figure 4. The dominant contribution has been a warming from GHG, with a best guess of about 1.5 K, which has been accompanied by a cooling due to SUL of probably about two thirds that magnitude. Any SOL or VOL contribution to the warming is small, with VOL restricted by the lack of volcanic eruptions immediately preceding either 1901 or 2004.

[13] The observationally constrained estimates of global SAT change over the past century are shown in Figure 5. The tighter constraints during the 1961–1990 interval arise from its use as the climatological base period. The warming periods in the early and late parts of the twentieth century are visible, as is the stable interval in between. Also shown are the estimates of future warming under the IPCC SRES A1B emissions scenario. Under traditional detection and attribution studies with GCMs, such estimates of future warming are important because the response amplitudes are constrained by the observed record of past changes, with only the response patterns determined from the GCM [*Allen et al.*, 2000; *Stott and Kettleborough*, 2002]. However, here we derived the response patterns directly from the observations without recourse to GCM simulations. Therefore this estimate represents a more fully observationally constrained estimate of future climate, with only the quantification of the uncertainty requiring the use of GCMs. The predicted warming of 2–7 K is comparable to the predictions of Stone et al. (submitted manuscript, 2005b) for this scenario using GCM estimates of the response patterns, indicating that the results are robust against model complexity.

4. Summary and Discussion

[14] While GCM output was not used for the estimation of the temporal response patterns to the various forcings, GCM control simulations were still necessary in order to estimate the magnitude of the internal variability of the climate system and thus the uncertainty in our attribution results. Furthermore, simple climate models, in the form of EBMs, were also necessary in order to convert forcing information into temperature responses. In the EBM all types of response processes are lumped together as a single simple radiative-thermodynamic process and cannot evolve separately. While this may be a fair approximation on an annual global mean scale, it nevertheless represents a major deficiency. However, the advantage of the EBMs is that they can be tuned to the observational record, and so inasmuch as the climate system is constrained by these radiative constraints on global climate scales, it is possible

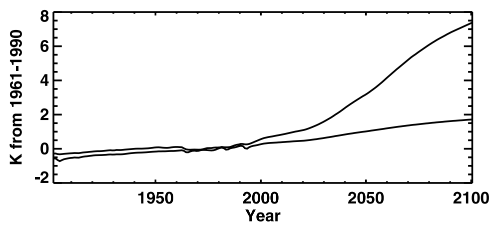

Figure 5. The estimated 90% confidence interval of global annual mean SAT climate from 1901 to present and through to 2100 assuming the SRES A1B scenario.

in practice for us to obtain an objectively calibrated version of the model. The results are qualitatively similar when a version of the EBM with k_i set to zero is used (with the exception of VOL with its high frequency forcing), supporting the robustness of the results.

[15] This analysis followed the methodology of Stone et al. (submitted manuscript, 2005a), which is designed to adapt climate information that is otherwise inappropriate for detection and attribution studies into a format that can be used in traditional methods. While it is designed for use with GCM output, it has also proved useful here when applied directly to the observational record. However, by first extracting responses from the observational record and them comparing them back to the observations again, this procedure performs in two steps what should properly be performed in one. The circularity of this methodology is a general problem with attribution studies because the scientific community is a long way from producing realistic climate models based solely on first principles with no tuning of the output. In this study the circularity is highlighted because the model development and tuning is performed within the study itself, rather than externally. Developing a less circular methodology is a direction of future research but the intention of this study was to apply detection and attribution techniques currently applied with GCMs more directly to the observations. Thus, for now these results present further complementary evidence that recent results from detection and attribution studies are robust to the climate modelling system used.

[16] This paper presents a further study detecting the effects of various forcings on the observed SAT changes that does not require GCM simulations for estimation of the response patterns to those forcings. The effects of GHG, SUL, and VOL forcing are detected, as in previous studies, although the SUL and VOL detection is probably sensitive to some sources of uncertainty that are not considered in this analysis. These results provide observational constraints with which to make quantifiable statements concerning past and future temperature changes. Altogether, these attribution and prediction results are consistent with those obtained when the same methodology is applied to GCM output (Stone et al., submitted manuscript, 2005b) or when a more simple EBM is used, indicating robustness of current results against model complexity.

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