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Technical Report
RAL-TR-1999-084

Uncertainty in Forecasts of Anthropogenic Climate Change

M R Allen P A Stott J F B Mitchell R Schnur and T L Delworth

17th January 2000

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ISSN 1358-6254

Uncertainty in forecasts of anthropogenic climate change

Myles R. Allen*
Space Science and Technology Department, Rutherford Appleton Laboratory

Peter A. Stott and John F. B. Mitchell
Hadley Centre for Climate Prediction and Research

Reiner Schnur
Max-Planck-Institut für Meteorologie

Thomas L. Delworth
Geophysical Fluid Dynamics Laboratory

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We assess the range of anthropogenic warming rates over the coming 50 years which are consistent with the simulations of several climate models and the emerging signal of climate change in the observations. Reconciling the models with the observed signal improves agreement amongst the simulations and provides an objective estimate of uncertainty in each prediction. The use of pattern-based signals allows separate estimates of the contributions to forecast uncertainty from greenhouse warming and sulphate aerosol cooling. Since aerosol cooling has opposed greenhouse warming in the past, any reduction in sulphate emissions over the coming 50 years not only increases the "best guess" rate of global warming, but also significantly increases the uncertainty range because a wider range of future warming rates would then be consistent with the signal observed to date. The observed surface temperature signal is still too weak to place useful bounds on long-term equilibrium warming without additional information on the timescale of the climate response.

**Address for correspondence:* Space Science and Technology Department, Rutherford Appleton Laboratory, Chilton, Didcot, OX11 0QX, UK. m.r.allen@rl.ac.uk

Given a scenario of future greenhouse gas concentrations, the range of uncertainty in forecasts of anthropogenic climate change is generally estimated either from the intercomparison of opinions elicited from climate experts [1] or through perturbation analysis of simple [2, 3, 4, 5] or intermediate-complexity [6] climate models. The former approach is necessarily subjective, while relying on models that predict only a limited number of variables can make it difficult to separate out the roles of different contributors to climate change [2, 5].

More recently, uncertainty analyses have been couched in terms of the range of predictions from different atmosphere-ocean general circulation models (A-OGCMs). The first five squares in figure 1 show predicted global mean temperature in the decade 2036-46 relative to pre-industrial (control) climate for four A-OGCMs [7, 8, 9, 10] all driven with approximately the same scenario ("IS92a" [11, 12]) of greenhouse gas and sulphate aerosol (GS) concentrations (the fourth square shows the impact of the inclusion of indirect sulphate and tropospheric ozone concentrations in one model [9]).

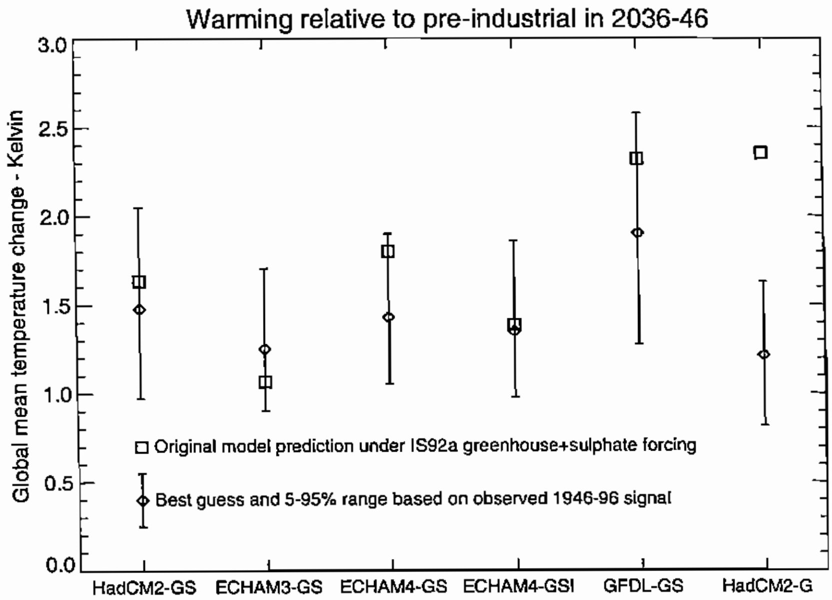

Figure 1: Squares: temperature change relative to pre-industrial (control) climate in a range of climate models for the decade 2036-46 under the "IS92a" scenario of greenhouse+sulphate forcing (greenhouse only in rightmost case). Diamonds: scaled temperature change after reconciling model-simulated large-scale patterns of near-surface temperature (expressed as anomalies about the 1896-1996 mean) over the five decades 1946-96 with the corresponding observed signal using an optimal fingerprint algorithm. Vertical bars: uncertainty in the scaled response based on uncertainty in the scaling factor required to reconcile the models with observed changes.

Predictions range from 1.1 to 2.3K, but translating inter-model spread into an objective uncertainty range is problematic because these models do not necessarily span the full range of behaviour consistent with current knowledge. Their climate sensitivities (equilibrium warming on doubling carbon dioxide), for example, all lie in the range 2.5-3.5K: a significantly smaller range than even the most optimistic current estimate of uncertainty in this parameter.

An alternative approach is suggested by the heavy solid line in figure 2. This shows how the predicted warming by 2036-46 under the IS92a GS scenario varies with the simulated rate of anthropogenic warming over the 20^{th} century as we vary the prescribed climate sensitivity in a simple climate model [2]. The plot is close to a straight line intercepting zero, indicating a simple linear relationship between the amplitude of the signal observed to date and the size of mid-21st-century warming. Almost the same relationship emerges if we assume a different rate of oceanic heat uptake [13] (heavy dotted line). Thus, in the context of this simple model, if the range of 20^{th} century warming trends attributable to anthropogenic influence were 0.25–0.5K/century, then the uncertainty range in 2040s temperatures would be 1–2K, irrespective of the accuracy of the model's climate sensitivity or timescale of oceanic adjustment.

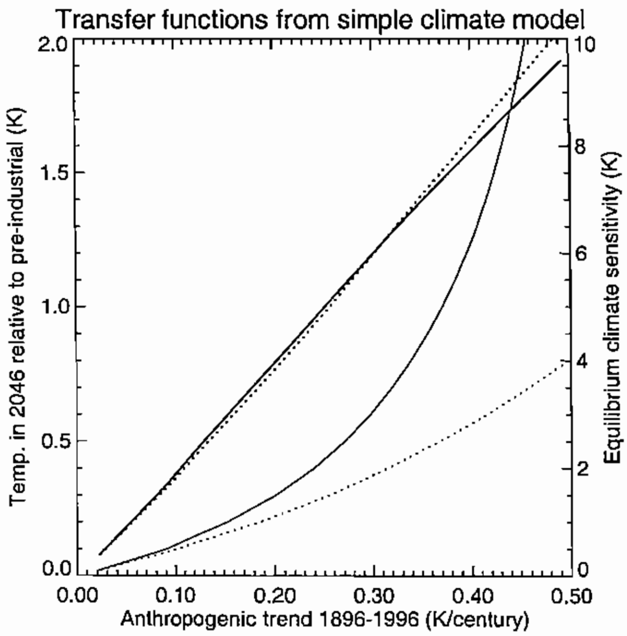

Figure 2: Heavy solid line, left-hand scale: Relationship between simulated global mean temperature trends over the period 1896-1996 and the predicted total anthropogenic warming by the decade 2036-46, obtained by varying the climate sensitivity in a simple climate model [2] under IS92a greenhouse and sulphate forcing. Heavy dotted line: relationship obtained assuming a different rate of oceanic heat uptake (effective vertical diffusivity of $0.25\text{m}^2/\text{s}$, vs. $2.0\text{m}^2/\text{s}$ in the base case). Light solid and dotted curves, right hand scale: corresponding relationships between simulated 1896-1996 temperature trends and equilibrium climate sensitivity.

In contrast, the relationship between the observed signal and the equilibrium climate sensitivity is both non-linear and dependent on the assumed rate of oceanic heat uptake. A 0.25–0.5K/century range in recent anthropogenic warming rates would translate into an uncertainty in sensitivity of 1.5–4K if we assume the faster timescale of oceanic adjustment (thin dotted line, right hand scale). With the slower timescale (thin solid line), no useful upper bound could be placed on the climate sensitivity on the basis of 20^{th} century temperature trends. Thus we cannot estimate climate sensitivity from recent observed surface temperature trends without an independent estimate of the timescale of oceanic adjustment [2, 13, 6]. Even if this response time were known, if it turns out to be towards the slower end of the current uncertainty range, then it may still be impossible to provide a useful upper bound on climate sensitivity on the basis of recent trends.

Figure 2 is derived from a very simple model, but we would expect similar relationships to hold in more complex systems provided both the strength of atmospheric feedbacks and the timescale of oceanic adjustment do not change in response to forcing of this magnitude. The fact that the majority of A-OGCMs give an almost linear response to a linear increase in radiative forcing (ref. [4], figure 6.4) provides some support for this assumption, but direct perturbation analysis of more complex models with realistic forcing trajectories is clearly required to explore its validity in full [14].

Confining our attention to the transient response, the problem now becomes: what fraction of the recent observed warming should be attributed to anthropogenic influence? Climate change detection techniques [15, 16, 17, 18, 19] provide an estimate of this fraction (or, more specifically, an estimate of the factor by which we have to scale a model-simulated trajectory to match the magnitude of the observed anthropogenic signal [20]), together with an objective estimate of the corresponding range of uncertainty.

The diamonds in figure 1 show the various model predictions for total warming by 2036-46 after scaling their respective trajectories to match the amplitude of observed near-surface temperatures (expressed as anomalies about the 1896-96 mean) over the 1946-96 period. By the mid-21^{st}-century, sampling uncertainty in the raw model predictions is small, particularly if ensemble simulations are available. Thus a factor-of-two uncertainty in the scaling required on the model-simulated 20^{th} century response translates into a factor-of-two uncertainty in the scaled prediction.

Rather than simply using temperature trends as a measure of the strength of the observed signal, we use a full spatio-temporal "fingerprint" [15, 19] of the various models' GS response. The use of a fingerprint pattern provides an "optimal estimate" [21] of the response amplitude, minimising uncertainty due to internal climate variability. Inter-model consistency is improved, with predictions from un-responsive models being scaled up and predictions from highly responsive models scaled down. The GFDL prediction remains high relative to the other models: in physical terms, this means that the model simulations are diverging by more than we would expect if they were simply scaled versions of the same underlying trajectory. The further we predict into the future, the greater this divergence is likely to be, so this approach is only valid over timescales up to the length of the observational record used. The estimated uncertainty in the amplitude of the scaled response is shown by the vertical bars. These are in less good agreement, reflecting differences between the models' estimates of internal climate variability.

To demonstrate what happens if an important process is omitted, the sixth square in figure 1a shows the predicted 2036-46 warming from the HadCM2 model forced with rising greenhouse gases alone. The raw prediction is over half a degree warmer than the same model under GS forcing, but the fingerprint analysis suggests that this model trajectory would need to be scaled down significantly to be consistent with recent observations. After application of this scaling, the resulting best-guess and uncertainty range is in better agreement with the GS simulations. This point is important because another, important but unknown, process may also have been omitted from all the GS simulations. Provided this process has a proportionally similar impact on the signal observed to date as on early 21^{st} century warming (as would be the case for an atmospheric feedback that scales with the surface temperature change) its omission from the models would not affect the estimated scaled prediction.

Errors which only manifest themselves in the future, such as a failure to represent a sudden shut-down in the thermohaline circulation, would not be accounted for in this analysis. At present, most simulated circulation changes appear to be relatively gradual over the timescales of interest [22], but the possibility of sudden non-linear climate change remains a crucial caveat and limits the forecast lead time over which it would be appropriate to pursue this approach. The assumption that the spatio-temporal patterns of response are independent of the response amplitude appears to be acceptable for large-scale surface temperature changes [16, 4], but it would not be valid for changes in precipitation [23] or atmospheric circulation [24], nor for cases in which the forcing changes abruptly over the period of interest.

Another important assumption underlying figure 1 is that the relative amplitude of the responses to greenhouse gases and to sulphate aerosols is as simulated in these GS experiments, so the combined response can be represented in each case by a single spatio-temporal pattern. Given the considerable uncertainty in the sulphate forcing and response, this is difficult to justify. For the HadCM2 climate model, we have separate multi-member ensemble simulations of the greenhouse-gas-only and the GS response. The fingerprinting approach allows separate estimates of the amplitude of both the greenhouse and sulphate signals in the observations, together with their joint uncertainty range [25]. By scaling their individual contributions to model-predicted future warming accordingly, we arrive at an uncertainty estimate which does not depend on the amplitude of the model-simulated response to either forcing agent.

Figure 3 shows the resulting range of uncertainty in the HadCM2 prediction of decadal global mean temperature relative to pre-industrial under the IS92a scenario. The solid line shows the original model prediction; the dashed line and shaded band show the median and 5–95% uncertainty range after scaling the simulated greenhouse and sulphate signals to match observed large-scale temperatures over the 1946-96 period. The observed spatially-averaged global mean temperatures of the five decades 1946-1996 are shown (diamonds) for illustration only: scaling factors are estimated from the full spatio-temporal pattern of temperature change. The figure shows range of uncertainty in the underlying anthropogenic trend: superimposed on this would be uncertainty in the temperature in individual decades due to internal variability, indicated by the vertical bars on the observations.

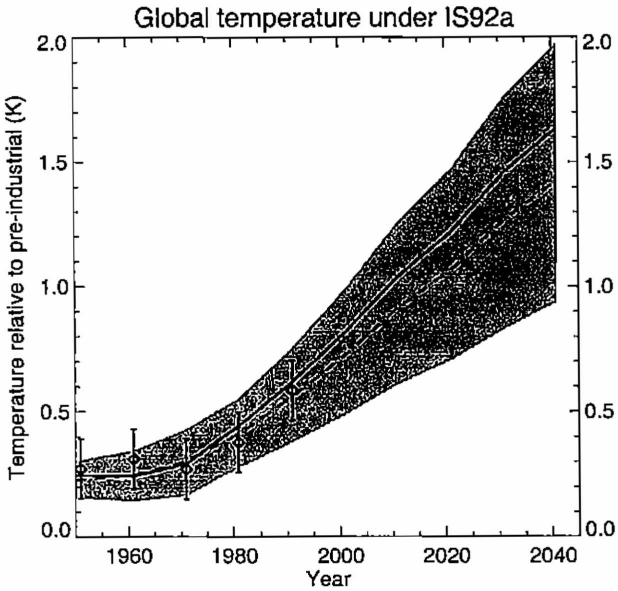

Figure 3: Simulation and forecast of decadal global mean temperatures relative to pre-industrial (control) as predicted by HadCM2 under the IS92a scenario. Solid line: mean of original 4-member ensemble simulation. Dashed line: after scaling the model-simulated spatio-temporal patterns of response to greenhouse and sulphate forcing individually to give the best combined fit to the observations over the 1946-96 period. Shaded band: 5-95% confidence interval on scaled response. Diamonds show observed decadal global mean temperatures (anomalies about the 1896-1996 mean, plotted about the corresponding mean of the ensemble); vertical bars show ± 2 s.d. of decadal mean temperatures from HadCM2 control.

Thus far, we have assumed that the observed record consists only of anthropogenic signals and internal variability. While this assumption is consistent with the available data [10, 19, 20], we have prior reason to expect natural external factors also to have affected temperatures over the 20th century [26, 18]. If we include the combined response (as estimated by HadCM2 [19]) to solar variability and volcanic aerosols in a three-way fingerprint analysis [27], the uncertainty range is almost unchanged because the inclusion of this estimate of the natural signal does not have a detectable impact on this estimate of the amplitude of the anthropogenic response (the use of decadal mean data minimises the impact of individual volcanic eruptions and the 11-year solar cycle). Nevertheless, uncertainty in the amplitude of the response to natural forcing (and thus the fraction of recent warming attributable to anthropogenic influence) remains an important caveat.

Surprisingly, estimating the greenhouse and sulphate signal amplitudes separately does not appear to increase forecast uncertainty: the forecast warming range by 2036-46 in figure 3 is almost identical to the range based on the HadCM2-GS simulation alone shown in figure 1. The reason is that the combination of greenhouse warming and sulphate cooling predicted under the IS92a emissions scenario happens to be particularly well constrained by the observed signal (at the global level – this would not necessarily be the case for regional changes). This is shown graphically in figure 4. The dotted contours show how projected warming over the 1996-2046 period depends on the scaling factors applied to the model-simulated greenhouse and sulphate signals. The raw model prediction is a 1.35K greenhouse warming and a 0.35K sulphate cooling over this period, giving a net warming assuming both scaling factors are unity of 1K (the square). If we scale the sulphate signal (either up or down) faster (by a factor of 1.35/0.35) than we scale the greenhouse signal, the net warming is unchanged: hence the orientation of the contours.

The cross and shaded region show the best guess and joint 90% uncertainty range on the scaling factors required on the model-simulated greenhouse and sulphate response-patterns to reproduce observed temperatures over the 1946-96 period. The uncertainty range is strongly tilted, meaning the model could over- (or under-)estimate the magnitude of recent greenhouse warming and still be consistent with the observed signal provided it also over- (under-)estimates the magnitude of sulphate cooling. The principal axis of the uncertainty region is close to parallel to the contours of future warming, so uncertainty in predicted warming under the IS92a scenario is relatively low (best-guess and 5-95% range shown by the diamond and solid bar).

Any reduction in future sulphate cooling not only increases the best-guess net future warming, but it also substantially increases the uncertainty range. The reason is that the two-dimensional confidence region would no longer be so well aligned with the isolines of predicted warming. For example, if the predicted 0.35K cooling due to sulphates over the 1996-2046 period is eliminated altogether (making the contours in figure 4 vertical), the best guess net warming over this period increases by 0.2K, or about 20% (less than

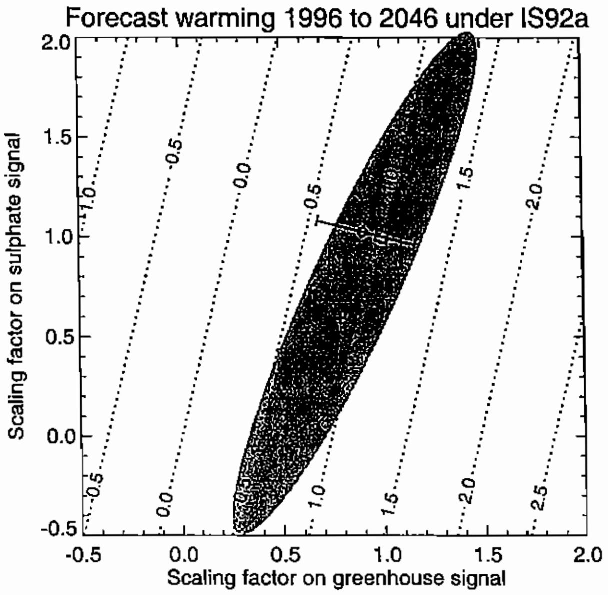

Figure 4: Dotted contours: isolines of global mean warming (in Kelvin) between the decade 1986-96 and the decade 2036-46 as a function of the scaling factors applied to the raw HadCM2 prediction of a 1K warming (square). Cross and shaded region: best-guess and joint 90% confidence region on estimated scaling factors required to reproduce observed large-scale near-surface temperatures over the 1946-96 period using response-patterns simulated by HadCM2. Diamond and solid error bar: best-guess and 5-95% range on forecast warming (read off from the contours) obtained by a probability-weighted sum of "allowed" scaling factors along the isolines of future warming.

0.35K because the best-guess scaling on the sulphate signal in figure 4 is 0.6), whereas the upper bound on the 5–95% range increases by almost 50%, from 1.2 to 1.7K. This would also be the case for other factors, such as stratospheric ozone depletion, whose influence on climate is less easy to detect than the agents considered here [20], but in which trends are also expected to reverse over the next few years.

Methods

HadCM2-GS [12] and GFDL-GS [10] simulations are based on 4- and 5-member ensembles respectively forced with observed greenhouse and parameterised direct sulphate forcing to 1990 followed by 1%/year compound increase in CO_2 (close to the IS92a scenario in terms of radiative forcing [23]) and IS92a projected sulphate loadings. ECHAM3-GS two-member ensemble [8] and ECHAM4-GS single simulation [9] are both based on observations followed by IS92a; ECHAM4-GSI single simulation [9] includes the impact of indirect sulphate forcing and tropospheric ozone changes. Model-observation comparison is based on decadal mean near-surface temperatures over the period 1946-1996. Data are expressed as departures from the 1896-1996 mean, which exploits the fact that recent decades have been generally warmer than the preceding half-century without attempting to fit the details of surface temperature changes in poorly-sampled earlier decades. Ensemble members and 100-year segments of the control were masked with the pattern of missing data in the observations before computing means and anomalies, filtered to retain only scales greater than 5,000km [28, 19] and projected onto the 10 leading modes of internal spatio-temporal variability of the individual model control simulations (ECHAM3 control used for ECHAM4). Scaling factors (diamond/square ratios in figure 3) are estimated using standard optimal fingerprinting [15] modified to account for the presence of sampling noise in model-simulated signals [29, 30]. Uncertainty estimates reflect uncertainty in scaling factors given interdecadal variability in the individual model control simulations (HadCM2: 1700 years, ECHAM3: 1900 years, GFDL: 1000 years). In each case the first half of the control was used to define the detection space and for optimisation, the second for uncertainty analysis.

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