Constraining climate forecasts: The role of prior assumptions

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[1] Any attempt to estimate climate sensitivity using observations requires a set of models or model-versions that simultaneously predict both climate sensitivity and some observable quantity(-ies) given a range of values of unknown climate system properties, represented by choices of parameters, subsystems or even entire models. The choices researchers make with respect to these unknown properties play a crucial role in conditioning their climate forecasts. We show that any probabilistic estimate of climate sensitivity, and hence of the risk that a given greenhouse gas stabilisation level might result in a "dangerous" equilibrium warming, is critically dependent on subjective prior assumptions of the investigators, not simply on constraints provided by actual climate observations. This apparent arbitrariness can be resolved by focussing on the intended purpose of the forecast: while uncertainty in long-term equilibrium warming remains high, an objectively determined 10–90% (5–95%) range of uncertainty in climate sensitivity that is relevant to forecasts of 21st century transient warming under nearly all current emission scenarios is 1.4–4.1°C with a median of 2.4°C, in good agreement with the "traditional" range.

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[2] Climate sensitivity, or equilibrium warming due to a doubling of carbon dioxide (CO_2), is a key determinant of climate change [*Intergovernmental Panel on Climate Change* (*IPCC*), 2001; *Morgan and Keith*, 1995]. Studies [*Andronova and Schlesinger*, 2000; *Forest et al.*, 2002; *Knutti et al.*, 2002; *Gregory et al.*, 2002; *Murphy et al.*, 2004; *Stainforth et al.*, 2005] attempting to constrain climate sensitivity by comparing models with recent observations report a wide range of distributions. Here we show that much of this variation arises from different prior assumptions regarding climate sensitivity before any physical or observational constraints are applied, suggesting fundamental reasons why a universal consensus on long-term equilibrium warming consistent with any given stabilisation level for greenhouse gases may prove impossible to achieve.

[3] We demonstrate our point with a simple global energy balance model (EBM) and diffusive ocean [*Hansen et al.*, 1985], although the reasoning applies to any model in which atmospheric feedbacks scale linearly with surface warming and in which effective oceanic heat capacity is approximately constant under 20th century climate forcing. The diamonds in Figures 1a and 1b show the average warming trend caused by greenhouse gas increase over the 20th century (vertical axis) as a function of effective heat capacity of the troposphere-land-ocean system (horizontal) and the climate sensitivity S (colours) for a range of different settings of model parameters. The black contour encloses the region consistent (at the 5% level) with observations of 20th century greenhouse warming and the effective heat capacity.

[4] We isolate the greenhouse warming signal using a pattern-based attribution analysis [*Stott and Kettleborough*, 2002] allowing for uncertainty in both greenhouse and other forcings [*Allen et al.*, 2000]. This estimate of attributable warming does not depend on climate sensitivity, although it does rely on the accuracy of patterns of temperature change and variability simulated by a climate model. The use of attributable warming as our temperature variable allows us to avoid problems associated with uncertainty in sulphate forcing [*Gregory et al.*, 2002], because future warming is more directly related to past greenhouse warming than it is to total twentieth century warming. Heat capacity is inferred from the observed change in global mean heat content [*Levitus et al.*, 2000, 2005] over the 1957–94 period divided by the corresponding change in decadal-mean surface temperature, allowing for the uncertainty in both quantities. Model parameters are chosen to sample heat capacity approximately uniformly, so the points are evenly spaced in the horizontal. The only difference between Figures 1a and 1b is the way we sample model parameters. In Figure 1a, following *Andronova and Schlesinger* [2000], *Forest et al.* [2002], and *Knutti et al.* [2002], parameters are chosen to sample S uniformly over the range 0.17 to 20°C.

[5] Weighting each of the runs in Figure 1a by the likelihood of obtaining these observations (specifically, the observed level of model-data discrepancy [*Forest et al.*, 2002]) if that combination of sensitivity and effective heat capacity is correct and estimating a "posterior" distribution for S from the weighted ensemble (the red curve in Figure 1c) gives a 5–95% range for climate sensitivity of 1.2–11.8°C. Two factors contribute to this high upper bound: First, for any given ocean heat capacity, the relationship between sensitivity and transient warming to date is nonlinear [*Stott and Kettleborough*, 2002; *Allen et al.*, 2000] which tends to concentrate the diamonds in Figure 1a at

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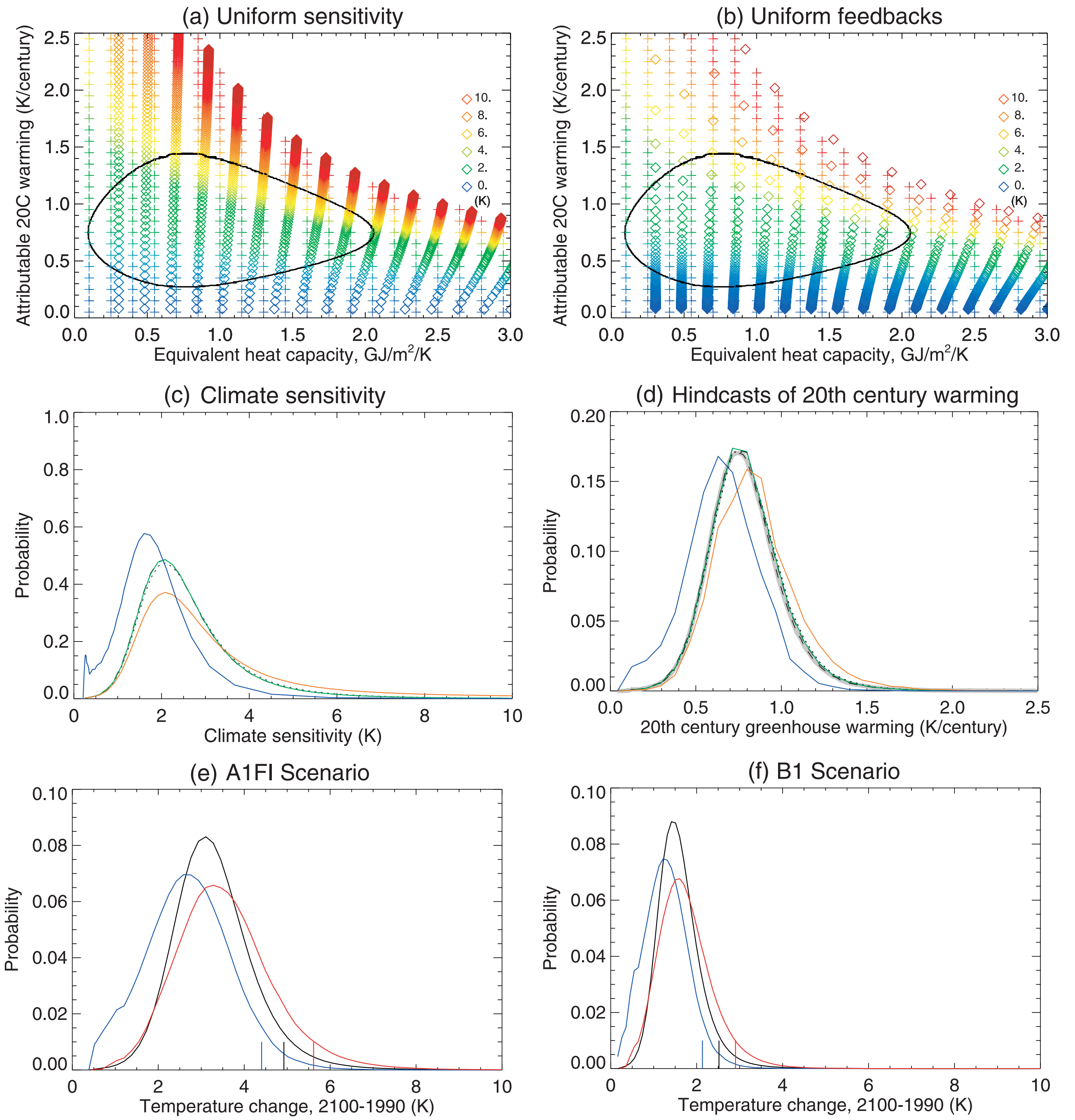

Figure 1. Relationship between climate sensitivity (colours), effective ocean heat capacity and 20th century warming attributable to changes in greenhouse gases. Diamonds show simulation results based on (a) uniform sampling of climate sensitivity, S, and (b) uniform sampling of feedback strength, or λ. Black contours enclose the region consistent with observations at the 5% level. Panel (c) shows distributions of climate sensitivity based on these observations, assuming a uniform initial distribution in sensitivity (red), in feedback strength (blue) and in attributable warming and heat capacity (black), as well as in forecast warming under the A1FI (black dotted) and B1 scenarios (black dashed) and in TCR (green curve). Panel (d) shows a reconstruction of the original data (thick grey curve) using assuming a neutral prior in sensitivity (red), feedback strength (blue) attributable warming (black solid line), A1FI (black dashed) and B1 scenarios (black dotted) and TCR (green). Panels (e) and (f) show 1990–2100 global mean temperature change under the A1FI and B1 scenarios respectively, starting from a uniform distribution for *S* (red), λ (blue) and forecast warming (black).

higher values of past warming. Second, this sampling of model parameters implies a uniform distribution for *S* before any comparison with observations, meaning a sensitivity between 2 and 3°C is assumed to be as likely as one between 3 and 4°C, or 9 and 10°C.

[6] *Murphy et al.* [2004] take a different approach: using a complex climate model they ran an ensemble of equilibrium 2xCO_2 experiments with expert-specified ranges of parameters, sampled parameters uniformly over these ranges and assumed that changes to parameters have an

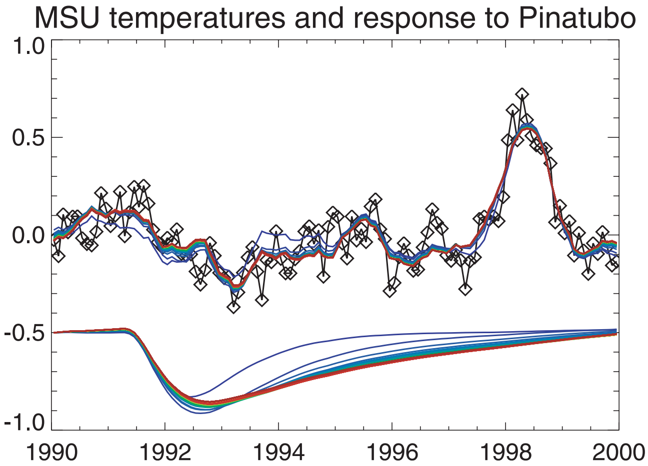

Figure 2. MSU channel 2 data (black diamonds) and best-fit timeseries for 20 values of climate sensitivity (colored as in figure 1), allowing Kv to adjust with the ENSO, trend and annual cycle coefficients for each value. Different choices regarding the baseline climate lead to different best fit sensitivities. Plotted below are the EBM runs for the cooling due to Pinatubo alone.

approximately linear impact on λ, the increase in energy radiated to space per degree of warming, which is proportional to $1/S$. If a single parameter dominates changes in λ, as is the case in our simple model (and as also happens to be the case by *Murphy et al.* [2004] for high sensitivities—another parameter change yields low sensitivities), these two assumptions, in this case, imply a sensitivity between 2 and 3°C is as likely, before any physical or observational constraints are applied, as one between 3 and 6°C, or between 1 and 1.2°C. The implications of such a uniform sampling of λ for our simple model are shown in Figure 1b: the relationship between sensitivity, warming and heat capacity is the same as in Figure 1a, but the location of the diamonds is very different. If we weight by comparison with observations as before, we now find a low chance (<1.4%) of a sensitivity greater than 4.5K (only a small fraction of diamonds enclosed by the contour are now yellow and orange). This leads to the blue distribution in Figure 1c and a 5–95% range for sensitivity of 0.6–4.0K.

[7] This result, failure to obtain a useful upper bound on climate sensitivity unless it is assumed a priori, is to be expected on simple physical grounds [*Hansen et al.*, 1985]: a Taylor expansion of the transient temperature response to any external forcing F given a constant effective heat capacity c and feedback parameter λ is proportional to $(\lambda dt)/c$. Thus, the first sensitivity-dependent term to emerge in the limit of high sensitivity, short timescale or high heat capacity (or any combination thereof) is proportional to λ, not S. A linear relationship between λ and climatology is assumed by *Murphy et al.* [2004] and explored further by *Stainforth et al.* [2005]. Despite reporting significant departures from linearity, both papers conclude that variations in climatology are much closer to linear in λ than S, again as would be expected from simple theory, so the same issues arise when climatology is used as a constraint in place of the transient response.

[8] If the relationship between the observational data and λ is linear, then the relationship between the data and S is nonlinear, with the rate of change dS/d(data tending towards zero as S increases. In practical terms, this means that a change in climate system properties that takes a 5°C to a 10°C sensitivity has less impact on any of these observable properties of the climate system than one that takes a 1.5°C to a 2°C sensitivity.

[9] These problems are even more acute in attempts to constrain sensitivity using shorter-term responses: Figure 2 shows the EBM response to forcing due to the Mt Pinatubo eruption in 1991. Studies [*Soden et al.*, 2002; *Lindzen and Giannitis*, 1998; *Douglass and Knox*, 2005] have attempted to use observations [*Christy et al.*, 2000] of the global mean temperature response to constrain sensitivity (usually after removing the ENSO signal [e.g., *Santer et al.*, 2001]). In our analysis, conducted using our EBM ensemble in conjunction with the MSU Channel 2 data [*Christy et al.*, 2000], we have allowed the baseline climate, background trend and ENSO signals to adjust to each EBM. Specifying the baseline, especially, can give the impression of a tight constraint, but given that we do not know how the climate of the 1990s would have evolved in the absence of Pinatubo, this, too, must be allowed to adjust. The result is that we still cannot rule out high sensitivities, confirming that volcanic forcing provides almost no constraint on sensitivity [*Wigley et al.*, 2005]. On physical grounds, one might expect the integrated cooling (the area between volcano-cooled and baseline climate, in degree-years) due to Pinatubo to scale more closely with climate sensitivity, and in the limit of an integration period much longer than c/λ, this is likely to be the case. The problem is, for high sensitivities (low λ), this corresponds to integration periods considerably longer than a decade, over which time the integrated noise due to internal climate variability is likely to overwhelm any signal. Cooling integrated over timescales shorter than c/λ scales with λ, not sensitivity, so the usual problems arise with using it to place an upper bound on sensitivity.

[10] Given that many parameters in climate models do not correspond to directly observable quantities for which we can define an objective prior distribution [*Kennedy and O'Hagan*, 2001; *Goldstein and Rougier*, 2004], equally plausible approaches using the same model and observations can yield very different estimates of the risk of a high climate sensitivity. This is an instance of Bertrand's paradox, one of the classic paradoxes of probability theory [*van Fraassen*, 1989; *Bertrand*, 1889; *Rosenkrantz*, 1977]. The solution, in this instance, is to make clear to the forecast user the relative roles of untestable prior assumptions versus observational or physical constraints. Unless they are warned otherwise, users will expect and answer to the question "what does this study tell me about X, given no knowledge of X before the study was performed?" This requires sampling non-observable parameters to simulate a uniform distribution in X, the forecast quantity of interest, before other constraints are applied, not the incidental system parameters that are used to derive it. Starting from a uniform distribution of S [*Andronova and Schlesinger*, 2000; *Forest et al.*, 2002; *Knutti et al.*, 2002] is appropriate

in and only in the special case of forecasting long-term equilibrium warming under a stabilisation scenario. Starting from a uniform distribution of λ [*Murphy et al.*, 2004] is more relevant to studies of atmospheric feedbacks or to quantifying the distribution of CO_2 concentrations consistent with a given temperature target.

[11] Neither sampling strategy is appropriate for hindcasts or forecasts of transient warming, since starting from a uniform distribution of S (or λ) introduces a bias towards high (low) warming rates that has nothing to do with either physical understanding or observations. This is illustrated in Figure 1d, which shows 20th century warming attributable to greenhouse gases based on observations (grey curve) and implied by the distributions in Figure 1c (red and blue curves). These hind-cast ensembles are biased with respect to the very observations that have been used to constrain them, as a result of the S and λ sampling. The solution is to resample or reweight the ensemble to simulate a uniform distribution in the quantity of interest (in this case hind-cast warming, as by *Gregory et al.* [2002]) before the observational constraints are applied (black curve).

[12] The implications of this point are shown by extending these weighted ensembles to 2100 under the IPCC A1FI (Figure 1e) and B1 1 (Figure 1f) scenarios [*IPCC*, 2001]. If we begin with a uniform distribution for S the weighted ensemble suggests a >8% (>3.5%) chance of 1990–2100 warming >5.0°C (>3.0°C) under the A1FI (B1) scenario. If we begin with a uniform distribution for λ the ensemble implies only a 1.2% (0.3%) chance of the same outcome. The approach we recommend here - sampling neutrally in the forecast quantity - implies the chances of 1990–2100 warming exceeding 5.0°C (3.0°C) under A1FI (B1) are 3.6% and 1.5%, respectively. This corresponds to the approach taken by *Allen et al.* [2000], *Stott and Kettleborough* [2002], and *Gregory et al.* [2002], who sampled uniformly in the observable quantities used to constrain the forecast, and yields the black distribution in Figure 1c and a chance of 1990–2100 warming exceeding 5.0°C (3.0°C) under A1FI (B1) of 3.6% and 1.5%, respectively. This agreement stems from the well-constrained relation between past and future warming under nonstabilisation scenarios [*Allen et al.*, 2000], so it is contingent upon the details of future emissions. If the data constraints were tighter, then the various predictive distributions would converge, although the theoretical problem would remain, and re-emerges as other variables are considered.

[13] The awkward conclusion is that we need a different sampling or weighting strategy for nonobservable parameters, corresponding to different prior assumptions, for different forecast variables and scenarios of future forcing, so there is no universally applicable distribution for climate sensitivity. If the focus is on equilibrium warming, then we cannot rule out high sensitivity, high heat uptake cases that are consistent with, but nonlinearly related to, 20th century observations. On the other hand, sampling parameters to simulate a uniform distribution of transient climate response (the global mean temperature change which results from a 1% per annum increase of CO_2 over 70 years) [*IPCC*, 2001], gives an approximately uniform distribution in much more immediately policy-relevant variables, including both past attributable warming and 1990–2100 warming under all SRES emissions scenarios. After weighting by observations as before, this approach implies a 5–95% range of uncertainty in S of 1.2–5.2°C, with a median of 2.3°C, suggesting traditional heuristic ranges of uncertainty in S [*IPCC*, 2001], may have greater relevance to medium-term policy issues than recent more formal estimates based on explicit uniform prior distributions in either S or λ. This is not to suggest that formal estimates of uncertainty are unnecessary, but rather that their applicability in practical forecasting has been limited by the problem outlined in this paper. Once the link between the purpose of the forecast and appropriate prior is clarified, the relationship between traditional heuristic ranges and formal uncertainty estimates becomes clear.

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