Using multiple observationally-based constraints to estimate climate sensitivity

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Climate sensitivity has been subjectively estimated to be likely to lie in the range of 1.5-4.5°C, and this uncertainty contributes a substantial part of the total uncertainty in climate change projections over the coming century. Objective observationally-based estimates have so far failed to improve on this upper bound, with many estimates even suggesting a significant probability of climate sensitivity exceeding 6°C. In this paper, we show how it is possible to greatly reduce this uncertainty by using Bayes' Theorem to combine several independent lines of evidence. Based on some conservative assumptions regarding the value of independent estimates, we conclude that climate sensitivity is very unlikely ($< 5\%$ probability) to exceed 4.5°C. We cannot assign a significant probability to climate sensitivity exceeding 6°C without making what appear to be wholly unrealistic exaggerations about the uncertainties involved. This represents a significant lowering of the previously-estimated bound.

1. Introduction

A subjective estimate that climate sensitivity (defined as the globally-averaged equilibrium temperature change in response to a doubling of atmospheric CO_2) is likely to lie in the range of 1.5–4.5°C was originally proposed in 1979 [*NAS*, 1979], and this estimate has essentially remained unchallenged ever since [eg *Houghton et al.*, 2001]. Recently, there has been an increasing focus on the potential of observationally-derived constraints to generate a more objective estimate of climate sensitivity. Many different approaches have been tried, but for the most part, even though most agree that the maximum likelihood estimate is close to 3°C, they have also concluded that the upper limit of climate sensitivity is difficult to constrain, with most estimates unable to rule out a climate sensitivity as high as 6°C at the 95% confidence level, and many reaching even higher levels [*Andronova and Schlesinger*, 2001; *Knutti et al.*, 2002; *Gregory et al.*, 2002; *Forest et al.*, 2002; *Frame et al.*, 2005]. Such a high value for climate sensitivity would be likely to have severe repercussions for the climate system over the coming century. However, most of these estimates were based on a small subset of the total body of evidence which we have concerning the behaviour of the climate system, and using such a subset in isolation in this way is equivalent to asserting that there is no useful information available other than that which was used in the creation of that particular estimate. Clearly, such an approximation is in principle bound to inflate the uncertainty of the overall estimate, but the magnitude of this effect has not been previously investigated. There are now several independent lines of evidence which can be used to provide estimates for climate sensitivity, and they can therefore be combined using Bayes' Theorem [*Papoulis*, 1984]. In this paper, we show that when this is performed, the uncertainty in climate sensitivity can be greatly reduced. Due to our decision to exclude some potentially useful but currently tentative information, we consider it likely that the resulting uncertainty estimate is still generous, although clearly our results rely on a number of subjective decisions.

In the following section, we briefly introduce the methods used. We then survey some recent attempts to estimate climate sensitivity using several different approaches: the global temperature trend over the last century; short-term cooling following volcanic eruptions; the climate at the Last Glacial Maximum; modern climatological patterns; and the global temperature change in the Maunder Minimum. These estimates are based on independent observations and widely varying physical phenomena: the heat balance of a warming planet; the feedbacks involved in short-term radiative perturbations; and quasi-equilibrium climate states under different boundary conditions. In order to generate a robust estimate, we attempt to err on the side of increased uncertainty when forming our constraints (which contain a necessarily subjective element), but not to such an extent as to completely devalue the information that the data provide. Finally, we demonstrate how the evidence can be combined to generate an estimate which is considerably more confident than any one line of argument alone can provide, and demonstrate the robustness of our result.

2. Methods

Bayes' Theorem tells us how to update a probabilistic estimate for an unknown variable x (such as climate sensitivity) in the light of new information [*Papoulis*, 1984]:

$$f(x|O,H) = f(O|x,H)f(x|H)/f(O|H)$$

where $f(x|H)$ is our prior estimate of the distribution of x (based on the history of previously accumulated evidence H) and O is a new observation. We note that in the case where the new observation is conditionally independent of previous data for a given climate sensitivity, $f(O|x, H)$ is precisely $f(O|x)$, which is the likelihood of x given O. So we can iteratively combine new information with a prior probabilistic estimate simply by multiplying the prior pdf with the likelihood function arising from the new data, and renormalising appropriately, as *Forest et al.* [2002] did for separate records of 20th century temperature change.

3. Observational constraints

3.1. 20th century warming

Many studies have attempted to estimate climate sensitivity using the overall warming trend of the last several decades or century, using a range of models, methods and prior assumptions [*Knutti et al.*, 2002; *Gregory et al.*, 2002; *Andronova and Schlesinger*, 2001; *Forest et al.*, 2002]. The resulting pdfs have generally shown that the recent warming does not provide a useful constraint when compared to the long-established (albeit subjective) estimate of 1.5–4.5°C. One fundamental reason for this is that the net forcing is itself not well constrained, and in particular is not constrained well away from zero, due to the possibility of sulphate aerosols substantially cancelling out the greenhouse gas forcing. If the net forcing is small, then climate sensitivity would have to be very high to explain the observed warming. Nevertheless, the results rarely assign a high probability to values in excess of 10°C, and they generally point to a maximum likelihood value well within the conventional range. We use as a typical representative of this class of constraints a probabilistic estimate of (1,3,10) where in this notation, used throughout this paper, the central value indicates the maximum likelihood estimate in degrees Celsius and the outer values represent the limits of the 95% confidence interval for a pdf, or 95% of the area under the curve for a likelihood function. Since this distribution is strongly asymmetric, we use the gamma distribution as a parsimonious representation, using shape and scale parameters 3.2 and 1.36 (see Figure). We take this distribution as our prior with which additional information in the form of likelihood functions will be combined.

3.2. Volcanic cooling

The short-term large-scale cooling following volcanic eruptions has also recently been used to estimate climate sensitivity [*Wigley et al.*, 2005; *Frame et al.*, 2005; *Yokohata et al.*, 2005]. Although it might appear that this information is already implicit in the 20th century reconstructions, those papers generally did not consider the short-term temperature changes in detail, instead relying largely on a long-term energy balance. Therefore we consider it reasonable to treat this constraint as a physically and observationally independent one. The impact of this assumption is discussed further in Section 4. *Wigley et al.* [2005] use a simple energy balance model (MAGICC) with a variable climate sensitivity parameter, and simulate the eruptions of Agung, El Chichon and Pinatubo. A comparison with the observed cooling produces a plausible range for each individual eruption which in each case gives a high likelihood to values close to 3°C, with an upper limit ranging from 5.2–7.7°C and a lower limit of 0.3–1.8°C. In principle, the three estimates could themselves be combined into an estimate which has significantly tighter limits of about (1.8,2.8,4.4). However, their analysis does not consider the issue of model error, which suggests they may have overestimated the precision of their estimates, and moreover implies that the uncertainties on the three estimates may not be wholly independent. On the other hand, theoretical considerations and simulations with a range of different models [*Frame et al.*, 2005; *Yokohata et al.*, 2005] confirm that a sensitivity in the region of 6°C or more implies a long cool period over several years which is not seen in the observational record. Although as *Frame et al.* [2005] remark, natural variability could potentially oppose and obscure this forced response for a single eruption, it is highly unlikely for this to have happened for each eruption in the historical record. We therefore use a gamma function with shape and scale parameters 8.5 and 0.40 as our likelihood function (see Figure). The shape of this function is described by (1.5,3,6).

3.3. Last Glacial Maximum

Temperatures at the Last Glacial Maximum (LGM) were substantially lower than the modern pre-industrial state for an extended period. However, temperature estimates are imprecise and rely on interpretation of proxy data. Recent syntheses of tropical data [*Ballantyne et al.*, 2005] indicate a cooling in this region of about 2.7°C relative to the pre-industrial state for sea surface temperatures, and 5°C over land. The cooling increases at higher latitudes, giving an average of 5.7–8.7°C over the northern hemisphere continents [*Bintanja and de Wal*, 2005]. Given this evidence, a range of (3,6,9) for the globally-averaged cooling is surely robust, with the true value likely to be near the middle of this the range. The main changes in radiative forcing at the LGM are about due to lower GHG levels and large ice sheets over the northern hemisphere, which each account for about -3Wm^{-2} [*Taylor et al.*, 2000] but changes in vegetation and dust also each add a little over -1Wm^{-2} [*Crucifix and Hewitt*, 2005; *Claquin et al.*, 2003], giving a net radiative forcing estimated at 6-11Wm^{-2}, which we describe as (6,8.5,11). The distributions for temperature change and forcing are symmetric, and so we model them as Gaussian distributions. Assuming independent uncertainties in these distributions, the pro-rata temperature change for a 3.8Wm^{-2} forcing (equivalent to a doubling of CO_2) can be described by (1.3,2.7,4.6).

We must, however, consider that the substantially different climate state and topography at the LGM, combined with the different seasonal and spatial pattern of forcing, might result in a somewhat different sensitivity to radiative forcing at the LGM as compared to a future warmer climate, and a range of model results bear this out. For example, results obtained by varying parameters in a GCM [*Annan et al.*, 2005] indicate that although there is clear correlation between climate changes for the LGM and doubled CO_2, there is also uncertainty of the order of 0.8°C (one standard deviation) in this single model's response. A much tighter correlation between past and future climates has been obtained using a simpler model [*von Deimling et al.*, 2005], but the relationship itself is a somewhat different one (different forcings will explain much of this discrepancy, however). Accounting for the possible difference between LGM and CO_2 sensitivities requires a subjective judgement based primarily on the range of model results. We add another 1.5 °C (independent, Gaussian, one standard deviation) error which we consider to generously cover the range of results available. With this additional factor, our likelihood function has the form (-0.6,2.7,6.1). This near-symmetric shape is well described by the Gaussian distribution with mean 2.7°C and standard deviation 1.7°C (see Figure).

3.4. Other constraints

There are at least two other lines of evidence that have been used in attempts to estimate climate sensitivity. Using large ensembles of model simulations with perturbed parameters, a link between modern climatology and climate sensitivity has been established by several researchers [*Murphy et al.*, 2004; *Knutti et al.*, 2005; *Piani et al.*, 2005]. Their resulting estimates for climate sensitivity typically indicate a maximum likelihood value of around 3–3.5°C, with 95% confidence limits of around 2 and 6°C. However, these results are all based on a single numerical model, the control version of which has a sensitivity of 3.4°C, and have yet to be more widely confirmed.

The Maunder Minimum (1645–1715) is a period when net radiative forcing is thought to have been significantly lower than today, for sufficiently long for the climate to approach a near-equilibrium state. The simulation of *Rind et al.* [2004] (using a model with a climate sensitivity of 4.7°C) appears to show too strong a cooling, even when compared to the cooler proxy reconstruction of *Moberg et al.* [2005], with an implied best estimate of around 3°C. The simulation of *Crowley* [2000] also suggests that 2°C is likely a little too low, but it would be rather speculative to turn these limited results into a likelihood function at this time. Also, one could legitimately question whether these estimates can be considered truly independent both of each other and the evidence already presented, since they have a significant dependence on model results which may share similar biases. Nevertheless, these data do support our other estimates and we will investigate how they could potentially affect the results.

4. Analysis and Discussion

None of the three constraints from sections 3.1–3.3 (with the two likelihood functions converted to pdfs under the assumption of a uniform prior) by itself rules out a climate sensitivity as high as 6°C at the 2.5% probability level, and one of them suggests that the probability of exceeding this value is greater than 20%. A naive analysis might conclude that such a high climate sensitivity cannot be reasonably ruled out by observations. However, such an analysis would be wholly mistaken, as each constraint only uses a small subset of the available evidence.

By construction, our prior based on 20th century warming, and the two likelihood functions, are based on independent data and methods. We can therefore combine their information simply by multiplying all the functions together and renormalising. We have performed this calculation numerically (see Figure). The resulting distribution can be represented by (1.7,2.9,4.9) in the format used throughout this paper. That is to say, it has a maximum likelihood value of 2.9°C, and, using the IPCC terminology for confidence levels, we find a likely range of 2.2-3.9°C (70% confidence) and a very likely range of 1.7-4.9°C (95%). We can also state that climate sensitivity is very likely to lie below 4.5°C (95%). These results represent a substantial decrease in uncertainty over those originally presented in *NAS* [1979] and in subsequent research. They also imply that the sensitivity range of modern GCMs (2.1-4.4°C) is likely to include the correct value (with greater than 80% confidence), and is very unlikely to exclude it by more than a small margin, thereby increasing our confidence in the models.

We must, however, consider the possibility that we have underestimated or even wholly excluded some sources of uncertainty in our calculation, so we investigate the robustness of the result to the use of different constraints. If, for example, we were to broaden the volcanic and LGM likelihoods to the point at which they are equivalent to the 20th century warming constraint (ie cube this gamma distribution), then we obtain the pdf indicated by the thin red dashed line. Even in this case, the probability of climate sensitivity exceeding 6°C is still below 4%. In order to justify such a wide likelihood for the volcanic constraint, we would have to claim either that a climate sensitivity of 10°C allows a rapid recovery of the surface temperature following a volcanic eruption (contrary to all the evidence from a range of models), or that natural variability has happened to strongly oppose (and never augment) the forced response for numerous individual eruptions. Furthermore, a $5\mathrm{Wm}^{-2}$ forcing and 10°C cooling at the LGM, which are both outside the ranges supported by the evidence, only imply a sensitivity of 7.6°C for $-3.8\mathrm{Wm}^{-2}$ forcing, so we would still require another 2.4°C difference between LGM and CO_2 sensitivities to satisfy the LGM constraint. Lastly, we have to completely ignore any evidence that the climatology and Maunder Minimum simulations provide. It seems to us that such assumptions cannot be considered reasonable, and yet even with them, climate sensitivity as high as 6°C is still very unlikely.

It also may be arguable that we are double-counting data in the 20th century and volcanic constraints, even though the data and methodologies of the former studies suggests this is unlikely to be a major effect. Using a uniform prior together with the volcanic and LGM data eliminates this possible risk, and only extends the 95% threshold to 4.7°C.

A more optimistic viewpoint would be to assume that the climatological and Maunder Minimum simulations can both be taken to imply usable and independent constraints equivalent to the volcanic likelihood which we have already used. The thin red dotted line shows the result that would arise if we were to apply two additional likelihood functions of this form in addition to those used in our original estimate. The tails of the distribution are narrowed somewhat, but the effect is not a huge one, with for example climate sensitivity very unlikely to exceed 4.1°C. The decision to exclude these additional constraints from our estimate suggests that our main results are unlikely to be overconfident.

5. Conclusion

We have demonstrated for the first time how multiple independent observationally-based estimates of climate sensitivity can be used to generate a substantially tighter bound than any previously presented. In forming our estimate, we have attempted to make robust and reasonable decisions, but they are necessarily subjective and some are based on a small number of quantitative estimates, so others may reasonably disagree as to their validity. However, the alternative option of excluding useful evidence when forming an estimate of climate sensitivity is equally subjective, and will inevitably result in exaggerated uncertainty in the results. We cannot assign a significant probability to climate sensitivity exceeding 6°C without making what appear to be wholly unreasonable assumptions to discard data and/or hugely inflate the uncertainties attached to a range of observational evidence. Even with generous uncertainty estimates, a value greater than 4.5°C seems very unlikely. In fact, our implied claim that climate sensitivity actually has as much as a 5% chance of exceeding 4.5°C is not a position that we would care to defend with any vigour, since even if it is hard to formally rule it out, we are unaware of any significant evidence in favour of such a high value. We hope that these results will encourage the further development of more robust and better quantified probabilistic interpretations of the various lines of evidence concerning the behaviour of the climate system.

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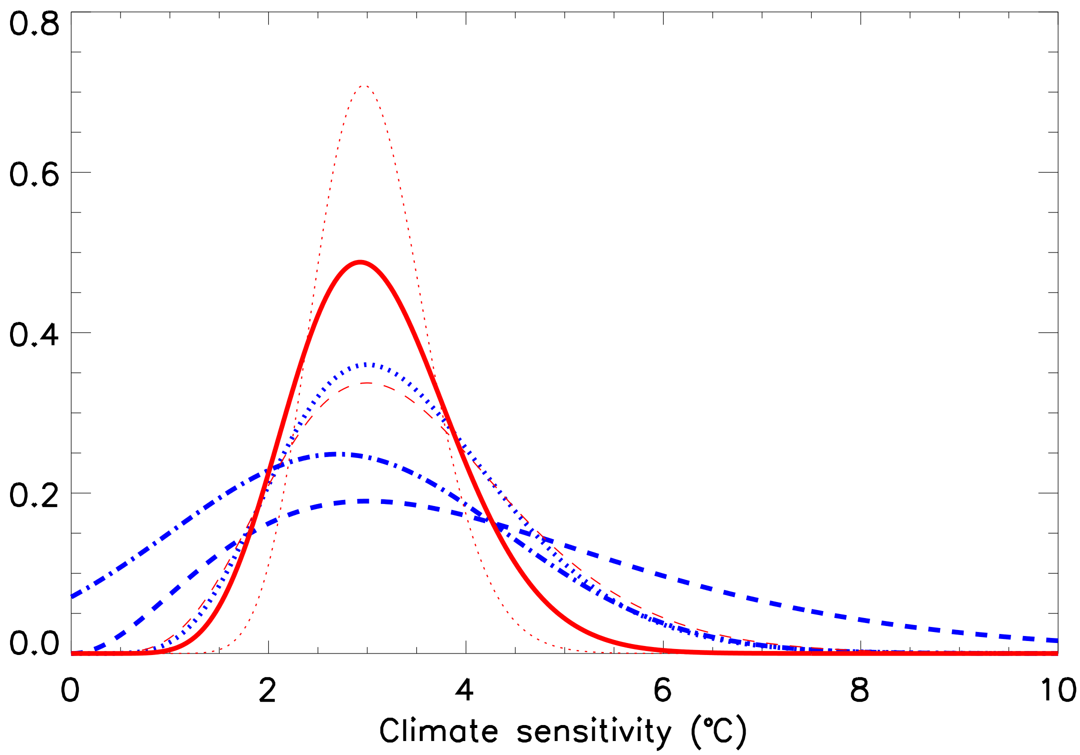

Figure 1. Pdfs and likelihood functions for climate sensitivity based on various observational constraints. Blue dashed line: 20th century warming (1,3,10). Blue dotted line: volcanic cooling (1.5,3,6). Blue dot-dashed line: LGM cooling (-0.6,2.7,6.1). Red solid line: combination of the three constraints (1.7,2.9,4.9). Thin red dashed line: combination of three copies of widest constraint (1.5,3.0,6.3). Thin red dotted line: five constraints (2.0,3.0,4.3). See text for details