Observational constraints on climate sensitivity

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Abstract

Climate sensitivity cannot be directly measured under present day conditions, since the real climate system will never been subjected to a sudden step change in carbon dioxide levels. Thus any attempt to estimate climate sensitivity using observations requires a model or set of models 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 parameters play a crucial role in conditioning their climate forecasts. This point has important practical implications. Any estimate 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, encapsulated in their predictive distributions for sensitivity, and not on constraints provided by actual climate observations. In contrast, the distribution of stabilisation levels consistent with a target temperature rise is well constrained by observations.

1. Bayesian formulation of estimates of climate sensitivity

Climate sensitivity S cannot be measured directly, since the real climate system will never been subjected to a sudden change in carbon dioxide levels, under present-day conditions, and then allowed to come to equilibrium. Thus any attempt to estimate climate sensitivity using observations requires a model or set of models that simultaneously predict both S 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 [1]. This model could be just a single energy conservation equation, through to a full general circulation climate model. The probability distribution function (PDF) for S given a set of observations, *data*, can then be expressed in terms of Bayes' Theorem:

$$P(S \mid data) = \frac{P(data \mid S) P(S)}{P(data)},$$

where $P(data \mid S)$ is proportional to the "likelihood" that these observations would be simulated by a model whose sensitivity lies within a small distance, dS, of S. In studies where a subset of otherwise equally plausible models all have the same sensitivity, $P(data \mid S)$ is simply the average likelihood of *data* taken across this subset. Given a "prior" sampling strategy for models or model-parameters, $P(S)$ is proportional the implied probability that the sensitivity is within dS of S before these data are considered. $P(data)$ is a constant required to ensure all probabilities sum to 100%.

2. The role of the prior or "predictive distribution"

The appropriate prior $P(S)$ is ambiguous, primarily because the observations used in *data* must play no role in the prior for Bayes' Theorem to apply, and it is impossible to separate prior beliefs about climate system properties from knowledge of relevant climate observations. This complicates the application of conventional methods of determining $P(S)$ such as expert elicitation [2]. The subjectivist paradigm is that the experts should not know about *data* when asked to provide a prior, but everyone in the climate field is familiar with basic observations such as the amount by which the world is thought to have warmed over the past century. Only the very simplest models can be set up without direct reference to climate data, and in these simple models the implications of any prior for *data* will be sufficiently transparent to be impossible for the expert to ignore. Climate observations are used extensively in the formulation and tuning of more complex models, in ways that are poorly documented and often obscure even to the model-developers themselves.

Given this problem, it is essential to distinguish the role of observational constraints from prior assumptions in policy guidance. Here we will focus on estimated likelihoods $P(data \mid S)$ from a range of studies. These are equivalent to estimated distributions for S if and only if the prior $P(S)$ is constant for all values of S over which the likelihood is non-zero. Such a "uniform" prior for S is used in many studies, despite not representing actual prior beliefs, because it makes clear the information provided by specific observations. This focus is also consistent with conventional climate change detection studies, which typically assume a uniform prior in warming attributable to greenhouse gases, even though physical reasoning would assign, for example, a low probability to greenhouse-induced cooling.

Evaluating $P(data \mid S)$ requires a representation of the expected discrepancy between actual observations and those simulated by the model due, for example, to observational uncertainty or internal climate variability. The magnitude of this "noise" term dictates how fast $P(data \mid S)$ declines as the model-data fit deteriorates away from the "best-fit" combination of parameters. Noise properties also cannot be observed directly, and must be based either on model-simulated variability (possibly augmented by information about the errors in observations) or estimated from residual model-data discrepancies. If modelled noise omits or underestimates sources of model-data discrepancy in the real world, uncertainties in S will be underestimated.

Figure (a) shows likelihood functions $P(data \mid S)$ from a range of studies [3,4,5,6,7] based on a wide range of data sources, normalised to have equal likelihood of S greater than 4K (hence focussing on how likelihood varies for above-expected sensitivities). These data sources include: various aspects of present-day climatology, the climate response to short-term volcanic forcing, the relationship between temperature changes and energy fluxes into and out of the atmosphere-ocean system, and the transient response to external forcing over the 20th century and over the past millennium. All studies show a highly asymmetric distribution, with low simulated values of S being inconsistent with these data sources, but only a relatively gentle decline of $P(data \mid S)$ towards high values of S . The similarity between the likelihood functions obtained by refs. [3], [6] and [7] is particularly striking given the wide disparity in methods and data sources used, and suggests some underlying explanation that goes beyond simple coincidence. Refs. [4] and [5] show a cut-off at 10K, but this was imposed in the way these studies were set up.

3. Short- and long-term forcing responses

The reason is indicated by figure (b), which shows exactly the same likelihood functions plotted against the climate feedback parameter, λ, or the additional energy radiated to space per degree of surface warming, which is inversely proportional to climate sensitivity. Because there is a one-to-one correspondence between λ and S, we can unambiguously equate $P(data \mid \lambda)$ with $P(data \mid S)$ if $S = F_{2xCO2} / \lambda$, where F_{2xCO2} is the radiative forcing due to doubling carbon dioxide. The distributions in figure (b) are much closer to Gaussian as we approach low values of λ, corresponding to high sensitivities, suggesting that, for all these data sources, observable properties of the climate system tend to vary linearly with λ rather than S, at least in the limit of high S. This result is confirmed by quantitative analysis of the properties of the upper tails of these distributions. It is also to be expected on physical grounds, at least for all studies focussing on the transient response: a simple Taylor expansion of the transient temperature response [9,10] to any external forcing F given a constant effective heat capacity c and feedback parameter λ:

$$c \frac{d\Delta T}{dt} = F - \lambda \Delta T$$

shows that the first sensitivity-dependent term to emerge in the limit of either high sensitivity, short timescale or high heat capacity (or any combination thereof) is proportional to λ, not S. There is no such simple explanation why observable aspects of climatology should scale with λ rather than S, but this is intuitively plausible since the same processes control climatology as control the top of atmosphere energy budget. This linear relationship between λ and climatology is assumed *a priori* in one study [7], and some evidence is emerging from large perturbed-physics ensembles to indicate that this assumption is justified.

Crucially, if the relationship between $data$ and λ is linear, then the relationship between $data$ and S is non-linear, with the rate of change $\partial(data)/\partial S$ tending towards zero as S increases. In practical terms, this means that a change in climate system properties that takes a 6K to a 10K sensitivity has very much less impact on any of these observable properties of the climate system than one that takes a 2K to a 6K sensitivity. In the majority of studies quoted, values of S in double figures would not be excluded at the 5% level if we begin by assuming all values of sensitivity are equally likely over the range zero to 15K. Hence, at present, the only way of ruling out these high values of equilibrium warming is *a priori*: they are not and, for many data sources, cannot be excluded by the comparison of models with observations.

The only potential data source that might provide a constraint giving a linear relationship between $data$ and S is the equilibrium response to changes in forcing over the Holocene or Glacial-Interglacial cycles [11]. So far, probabilistic studies evaluating how the likelihood of observed paleo-climate proxy data varies with assumed climate sensitivity have not been performed, so the effectiveness of this constraint in ruling out high sensitivities has not yet been determined. Any constraint based on Holocene or Last Glacial Maximum climate must assume, of course, that the sensitivity of the present-day climate to a forcing dominated by carbon dioxide change is the same as, or can be inferred directly from, the sensitivity to a change dominated by solar forcing and a combination of solar forcing and strong cryospheric feedbacks.

4. Implications for the definition of "dangerous climate change"

The fact that we cannot, on physical grounds, place a firm upper limit on climate sensitivity has important practical implications. Any estimate 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, encapsulated in $P(S)$, and not on constraints provided by actual climate observations. Hence it is premature to suggest we can provide an objective assessment of the risks associated with different stabilisation levels given the information provided by current climate observations. Note that this does not preclude an objective assessment of the risks of future transient climate change associated with specific concentration pathways: the problem of the non-linear relationship between observable quantities and forecast response applies specifically to stabilisation scenarios.

The linear relationship between $data$ and λ that applies over a wide range of data sources means that the distribution of atmospheric CO_2 concentrations consistent with a given temperature stabilisation target is much easier to constrain with presently-available observations than the distribution of equilibrium warming consistent with a given CO_2 concentration. The reason is that the first depends on λ , which is constrained by data, while the second depends on S , which is not. This has a very specific practical implication for the outcome of this workshop. It is much easier to quantify the risks associated with a strategy aiming at a given temperature target (for example, the risk of needing steeper, and hence more expensive, cuts in emissions in the future if the response turns out to be higher than expected), than it is to quantify the risks associated with a strategy aiming at a given stabilisation target (for example, the risk of that stabilisation target giving a higher-than-expected response).

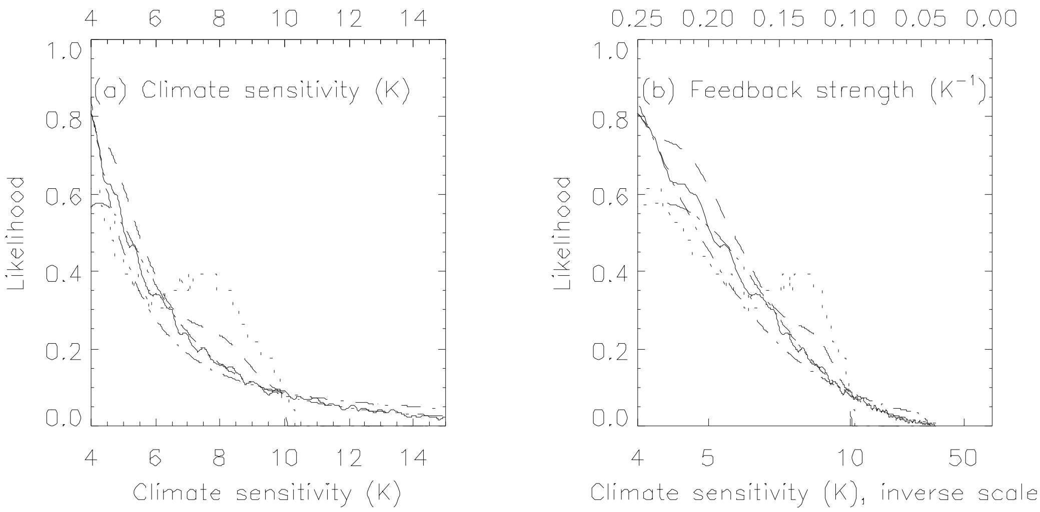

Figure: (a) Likelihood functions $P(data \mid S)$ for a range of studies and data sources plotted against S . These distributions are approximately equivalent to the distribution of possible equilibrium warming on a 550ppm CO_2 stabilisation scenario if all values for this warming are assumed equally likely before the constraint of the data is applied.

(b) Likelihood functions $P(data \mid \lambda)$ plotted against λ , expressed as $S^{-1} = \lambda / F_{2xCO2}$, which corresponds to the fractional increase in CO_2 concentration per degree of warming. These distributions are equivalent to the distribution of possible concentration targets consistent with a given temperature target if all concentration targets are assumed equally likely before the constraint of the data is applied. Note that while the distributions in (a) show "fat" upper tails, corresponding to a weak constraint, the distributions in (b) are much closer to Gaussian, indicating a direct link to the observable quantities used to constrain them.

5. References

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