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Uncertainty in climate sensitivity estimates due to random realizations of unresolved climate noise

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We evaluate how climate sensitivity (CS) estimates depend on unresolved climate noise (i. e. natural climate variability, observational errors, etc.). We use ensemble runs of the University of Victoria Earth System Climate Model (UVic ESCM) spanning the last two centuries where CS is systematically varied. Our approach accounts for the uncertainty in vertical ocean mixing and anthropogenic sulfate aerosol effects, and uses emulation to approximate model response at parameter values that are not sampled. We repeatedly construct pseudo-observations of global mean temperature and ocean heat content from model output at a specified 'true' CS. We re-estimate CS using the pseudo-observations and a Bayesian Markov Chain Monte Carlo (MCMC) method. We quantify how CS estimates depend on random realizations of the unresolved climate noise, assuming realistic climate system knowledge. For uniform priors, the standard deviation of CS modes is 1.6 deg. C, while for informative priors it is 0.41 deg. C.

1. Introduction

Future climate projections strongly depend on climate sensitivity (CS) [*Matthews and Caldeira*, 2007]. CS is often defined as the equilibrium global mean near-surface temperature change following the doubling of atmospheric CO_2 concentrations [*Andronova et al.*, 2007]. Current CS estimates are uncertain [*Forest et al.*, 2002; *Tomassini et al.*, 2007; *Olson et al.*, 2012]. This uncertainty arises in part from (i) climate model error, (ii) model emulator error, (iii) unresolved internal climate variability, and (iv) observational error. We refer to the sum of these processes as 'unresolved climate noise'. Climate sensitivity has been previously estimated by comparing climate model runs with observations using inverse methods [*Forest et al.*, 2002, 2006; *Knutti et al.*, 2003; *Tomassini et al.*, 2007; *Drignei et al.*, 2008; *Holden et al.*, 2010; *Olson et al.*, 2012, and others]. Typically, such studies also account for other key uncertainties controlling model response to CO_2 on the decadal and century timescales, such as vertical ocean mixing, and effects of anthropogenic sulfate aerosols. A Bayesian approach using Markov Chain Monte Carlo (MCMC) methods is often used to sample climate parameters [*Tomassini et al.*, 2007; *Urban and Keller*, 2010; *Olson et al.*, 2012] and to provide probability density functions (pdfs) for CS. While these studies break important new ground, they are silent on the question of the sensitivity of CS estimates to random realizations of unresolved climate noise.

Observation system simulation experiments (OSSEs) can be used to address this question. OSSEs refer to parameter estimation based on simulated datasets that are generated from a model with a given 'true' parameter value. Because in this case the 'truth' is known, OSSEs can be used to test the estimation method [*Huang et al.*, 2010a, b]. Furthermore, they can help in discovering non-identifiable parameters and biases in parameter estimates [e. g., *Huang et al.*, 2010a; *Serra et al.*, 2011; *Zakamska et al.*, 2011]. Unfortunately, the OSSEs have not been performed for climate sensitivity estimation, except for *Urban and Keller* [2009]. This study, however, does not explore the sensitivity of the results to random realizations of unresolved climate noise.

Here we use the OSSEs to evaluate the sensitivity of CS estimates to unresolved climate noise under a variety of assumptions. We improve on *Urban and Keller* [2009] by (i) considering the uncertainty in the anthropogenic sulfate aerosol effects, (ii) employing a more realistic Earth System model with a three-dimensional dynamic ocean component, and (iii) using more information from observational constraints.

2. Methods and Experimental Design

2.1. Overview

We use an ensemble of runs of an Earth System Model over the last two centuries where key climate parameters are systematically varied. Specifically, the parameters include background vertical ocean diffusivity (K_{bg}), climate sensitivity (CS), and a scaling factor for the effects of anthropogenic sulfates (A_{sc}). We employ a statistical approximator ('an emulator') to estimate model output at the parameter values where the model was not evaluated. Climate model emulators have been previously used by *Drignei et al.* [2008], *Holden et al.* [2010] and *Edwards et al.* [2011]. In a suite of OSSEs, we construct pseudo-observations of surface temperature and upper ocean heat content by contaminating model output at known true CS with unresolved climate noise. We then re-estimate CS using a Bayesian MCMC method of *Olson et al.* [2012]. In the re-estimation process each parameter setting Θ is associated with a likelihood $L(Y|\Theta)$ based on how well the corresponding emulator run compares with the pseudo-observations Y. Using the Bayes Theorem, the likelihood is combined with prior probability $p(\Theta)$ to generate posterior probability $p(\Theta|Y)$ for the parameter setting:

$$p(\Theta|Y) \propto L(Y|\Theta) \times p(\Theta). \tag{1}$$

The MCMC samples parameter space to create probability density functions (pdfs) for CS. We use this approach to address two main questions: (i) What is the sensitivity of CS estimates to random realizations of unresolved climate noise? and (ii) Does this uncertainty depend on the input CS? We give further details on the Earth System model, its emulator, historical simulations, MCMC, and experimental design in the following sections.

2.2. Earth System Model Simulations

We use the University of Victoria Earth System model (UVic ESCM) version 2.8 [*Weaver et al.*, 2001]. Our version of the model includes additional greenhouse gas, volcanic, and anthropogenic sulfate aerosol forcings, and a different solar forcing compared to the out-of-the-box code [*Olson et al.*, 2012]. Our analysis relies on an ensemble of 250 historical UVic ESCM runs over the last two centuries. The ensemble varies CS, along with background ocean diffusivity (K_{bg}) and a scaling factor for albedoes due anthropogenic sulfate aerosols (A_{sc}) as in *Olson et al.* [2012].

2.3. Gaussian Process Emulator

The MCMC method to estimate CS given the pseudo-observations requires orders of magnitude more UVic ESCM runs than the size of the ensemble. We hence need to estimate the UVic ESCM response at any desired parameter setting over the range of the ensemble. We use a Gaussian Process emulator, described in *Olson et al.* [2012] to this end. Specifically, the emulator estimates global average surface temperature anomalies (years 1850-2006, hereafter T) and upper ocean heat content anomalies (0-700 m, years 1950-2003, hereafter OHC700). These times reflect the coverage of pseudo-observations (Section 2.4) and are consistent with the span of available observations from *Brohan et al.* [2006] and *Domingues et al.* [2008]. The temperature anomaly is referenced to years 1850-1899, while the OHC700 anomaly - to years 1950-2003. We develop a separate emulator for the deep ocean heat content anomaly (0-3000 m, years 1953-1996, hereafter OHC3000). These times are chosen to match coverage of the historical observations from the *Gouretski and Koltermann* [2007] dataset. This anomaly is referenced with respect to 1953-1996 mean. Further information on the emulators is provided in the Auxiliary Material.

2.4. Observation System Simulation Experiments

CS pdfs provided in the literature typically rely on a single realization of the unresolved climate noise. We assess how potential pdfs look if we had different realizations of this noise (for example, if we lived in a different world, one with a different manifestation of interacting modes of climate variability, observation errors, etc.). We perform three observation system simulation experiments towards this purpose: 'Standard', 'Inf. Priors' and 'Higher CS'. The experiments share the same set-up, with relatively minor differences.

For all three experiments, we simulate pseudo-observations of T and OHC700 from the UVic ESCM (approximated by its emulator) with known CS, and re-estimate CS using Bayesian inference via MCMC. To construct the pseudo-observations, we superimpose realizations of unresolved climate noise on model output at true parameters for periods specified in Section 2.3. The unresolved climate noise is modeled as an AR(1) process. This process is specified by its innovation standard deviation σ and autocorrelation ρ. Here we adopt the modes of the *Olson et al.* [2012] base case estimates: $\sigma_T = 0.10$ [°C], $\sigma_{OHC700} = 2.6$ [$\times 10^{22}$ J], $\rho_T = 0.58$, and $\rho_{OHC700} = 0.079$. To re-estimate CS we adopt a simple statistical model where the model-data residuals are assumed to be an AR(1) process. Additional time-independent bias is assumed to exist between modeled and observed T. We re-estimate the parameters using MCMC. The MCMC is a procedure for efficient evaluation of posterior probability in multidimensional parameter space [*Metropolis et al.*, 1953; *Hastings*, 1970]. It can be used to construct posterior pdfs for climate model parameters. We repeat each of the experiments sixty times with different random realizations of the noise process.

The experiments differ in assumed true parameter values and in the priors (Table 1). For our 'Standard' experiment, we use mean estimates from the base case of *Olson et al.* [2012] as true parameters. These values are $K_{bg} = 0.19$ cm^{2}s^{-1}, CS = 3.1 °C and A_{sc} = 1.1. We use uniform priors for all parameters, to remove potential biasing effects due to non-uniform priors [*Hill et al.*, 2012]. 'Inf. Priors' differs from 'Standard' by using informative priors for CS (Figure 1) and K_{bg} following the default case of *Olson et al.* [2012]. 'Higher CS' experiment uses uniform priors, and a higher true CS. Specifically, we adopt $K_{bg} = 0.19$ cm^{2}s^{-1}, CS = 4.8 °C and $A_{sc} = 1.3$. These values are selected to be consistent with the bivariate joint pdfs presented in *Olson et al.* [2012].

As a sensitivity study, we perform two additional experiments substituting OHC3000 dataset for OHC700. Thus, the temperature and the deep ocean heat pseudo-observations are assimilated jointly. These cases are called 'Standard OHC3000' and 'High Noise OHC3000'. The details on these experiments are provided in the Auxiliary Material.

For each experiment, two realizations are tested for convergence by running the estimation twice with different initial values for the final MCMC chain. We have not detected any misconvergence problems with our algorithm.

3. Results

The estimated pdf for climate sensitivity depends critically on random realizations of the unresolved climate noise (Figures 1 and 2). We measure this second-order uncertainty by standard deviation of CS modes (Table 1). This uncertainty is robust with respect to priors, to the input true climate sensitivity value (Figure 1), and to the ocean heat content dataset (Figures S3 and S4 in the Auxiliary Material). This uncertainty ('Standard' and 'Higher CS', Figure 1) appears to exceed the one in the recent literature that also relies on uniform priors [*Hegerl et al.*, 2007]). This might be because the estimates from historical observations [*Hegerl et al.*, 2007] use a single realization of internal climate variability. To the extent this realization influences the estimates, these pdfs are statistically dependent. Any analysis not accounting for this potential dependence can result in overconfidence. Overall, our results suggest that there might be more uncertainty in the climate system than is suggested by previous climate parameter estimation studies.

The second order uncertainty increases at higher CS. Specifically, both pdf width and scatter increase considerably compared to the 'Standard' case (Table 1). This suggests that higher climate sensitivities can be difficult to detect if a particular realization of climate noise biases the result low. This is consistent with the results of *Hansen et al.* [1985]. In their simple model, at low CS, the CS strongly affects transient ocean warming due to CO_2. However, when the CS is high, its effect on the response is small since most of the warming is still in the pipeline. Thus, two markedly different high CS values can result in similar temperature response. It follows, that at higher climate sensitivities a small uncertainty in ocean surface warming implies, at a fixed ocean diffusivity, a larger uncertainty in climate sensitivity. Our model shows similar results for surface temperature warming as a function of CS at plausible A_{sc} values (results not shown). It is possible that other factors play a role in this increased uncertainty, such as a larger A_{sc} value in the 'Higher CS' case.

Using more realizations decreases the bias in average CS estimates. For example, the mean absolute bias of a mode of CS pdf in the 'Standard' experiment is 1.1 °C. However, when the modes are averaged between all 60 realizations, the bias is only 0.2 °C. This result is robust with respect to different assumptions, and occurs in all five OSSEs (Table 1). We note that in the real world, aggregating CS estimates based on different historical datasets might not decrease the bias. This is because all historical datasets stem from a single realization of internal climate variability. If this variability considerably biases the estimates, then combining the observations will not eliminate the bias.

Uniform prior experiments overestimate CS, while the 'Inf. Prior' case underestimates it (Table 1). We hypothesize that the overestimation biases in the uniform cases result from (i) the boundary effect (the distribution of the modes are truncated at the lower bound) and (ii) skewed distributions of the modes (Figures 2 and S4 in the Auxiliary Material). Similar effects were previously noted in the field of astrophysics by *Serra et al.* [2011] and *Zakamska et al.* [2011]. Note that while the mean CS modes are biased high, the modes and the medians of the CS modes generally appear to be close to the true input values (Figures 1, 2, S3, S4). More experiments with different climate models and input parameters are needed to assess whether this effect is a general feature that needs to be accounted for. Note that policy implication of the bias in the uniform case are limited because in the real world informative priors are typically used [e. g., *Sanso and Forest*, 2009; *Urban and Keller*, 2010; *Olson et al.*, 2012]. Here the informative priors appear to solve the overestimation problem (Figure 2, Table 1). However, they introduce a negative bias in the direction towards the prior mode. This indicates that careful consideration should be given to priors in the CS estimation process. More thorough examination of the effects of various priors is the subject of future work.

4. Caveats

Our analysis uses many simplifying assumptions that point to several caveats and open research questions. For example, our Earth System model relies on a number of approximations and does not use all historic forcings (i. e. indirect effects of anthropogenic sulfates; or tropospheric ozone [*Forster et al.*, 2007]). Furthermore, we do not account for past forcing uncertainties. Moreover, we change climate sensitivity by varying longwave radiative feedbacks, while shortwave feedbacks are also uncertain [*Bony et al.*, 2006]). In addition, our MCMC method excludes a potential cross-correlation among the residuals for different diagnostics. However, our exploratory data analysis suggests such correlations are likely weak. Also, we use a small number of realizations of the unresolved climate noise. Last, but not least, we rely on uniform priors in most of the experiments. We have chosen to work with the relatively simple prior specification because our focus is to study the sensitivity of our inference about CS to climate noise. It remains an open question to find informative priors that lead to good bias, variance, and coverage properties. Finally, we use a very limited set of assumptions about the input parameters. Specifically, we use only two climate parameter combinations, and do not sample the substantial uncertainty (e. g. *Olson et al.* [2012]) of the properties of unresolved climate noise. A much more systematic sampling of such uncertainties is needed to confirm our findings.

5. Conclusions

In this proof-of-concept study we use observation system simulation experiments to estimate climate sensitivity using UVic ESCM model runs and pseudo-observations of global average surface air temperature and ocean heat uptake. Our approach accounts for uncertainties in other key climate parameters: vertical ocean diffusivity and anthropogenic sulfate aerosol effects. Given the aforementioned caveats, we obtain two main results. First, given a known input climate parameter setting, there is a considerable second-order uncertainty in climate sensitivity estimates due to random realizations of unresolved climate noise. Second, this uncertainty increases considerably when higher input climate sensitivity and aerosol scaling are used. We suggest that simulation experiments with known input values be performed as part of climate parameter estimation studies as an additional testing step. Our method can be adapted to quantify the potential of future observation systems to constrain climate parameters.

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Table 1: Some specifications of observation system simulation experiments, and corresponding properties of posterior probability density functions for CS. All values are in °C. 'Unif.' refers to uniform priors for climate parameters, and 'Inf.' refers to informative priors for K_{bg} and CS following the default case of *Olson et al.* [2012]. Bold face indicates a significant bias ($\alpha = 0.05$). The mean 68% CI refers the mean 68% posterior credible interval of CS estimates. The interval is calculated as the range between the 16th and the 84th percentiles of the CS chains.

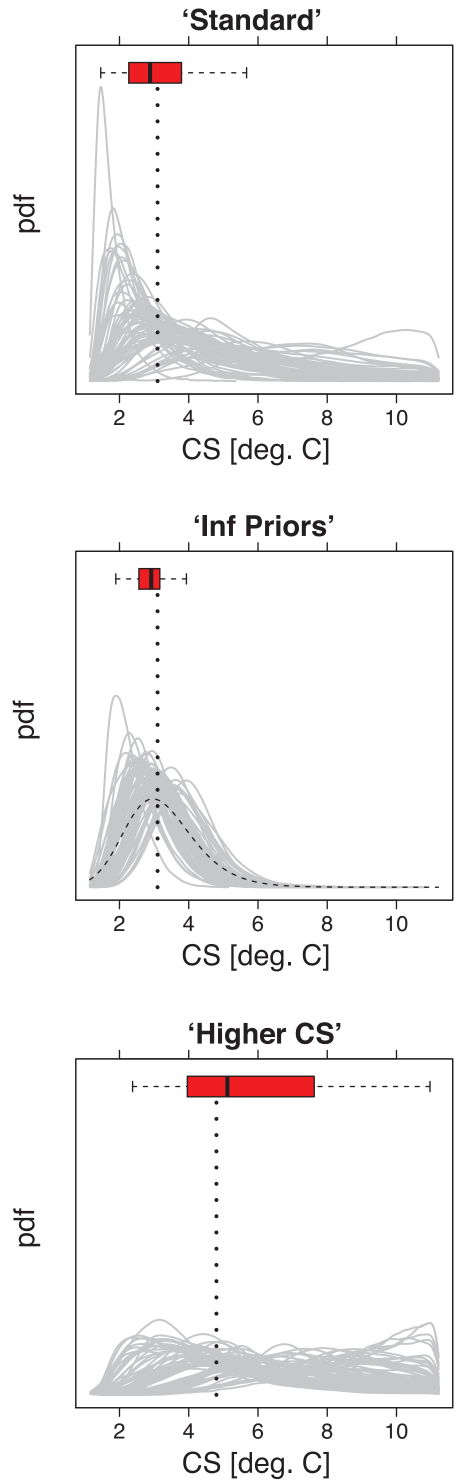
Experiment	Assumed true CS	Priors	Mean estimated CS mode	Mean absolute bias of estimated CS modes	Bias of mean estimated CS mode	Std. of estimated CS modes	Mean 68% CI of estimated CS pdfs
'Standard'	3.1	Unif.	3.3	1.1	0.2	1.6	3.5
'Inf. Priors'	3.1[a]	Inf.	2.9	0.36	**-0.2**	0.41	1.5
'Higher CS'	4.8	Unif.	5.8	2.0	**1.0**	2.6	4.5
'Standard OHC3000'	3.1	Unif.	3.6	1.3	**0.5**	1.8	4.3
'High Noise OHC3000'	3.1	Unif.	3.7	1.3	**0.6**	1.9	4.4

[a]While true input CS is 3.1 °C, the mean of the non-uniform prior is 3.25 °C, and the mode is 2.96 °C .

Figure Captions

Figure 1. Posterior probability distributions (pdfs) for climate sensitivity from observation system simulation experiments: (top) 'Standard', (center) 'Inf. Priors' and (bottom) 'Higher CS'. Each grey line corresponds to one realization of unresolved climate noise. True input climate sensitivities are shown by vertical dotted lines. The dashed pdf denotes CS prior in the 'Inf. Priors' experiment. The box plots show the distributions of estimated modes. The dashed whiskers extend to the most extreme data point that is no more than 1.5 interquartile ranges from the box. The limits of the y-axes are the same between panels.

Figure 2. Histograms of modes of climate sensitivity estimates: (top) 'Standard', (center) 'Inf. Priors' and (bottom) 'Higher CS'. True input climate sensitivities are shown by vertical red lines. Y-axes limits are the same between panels.



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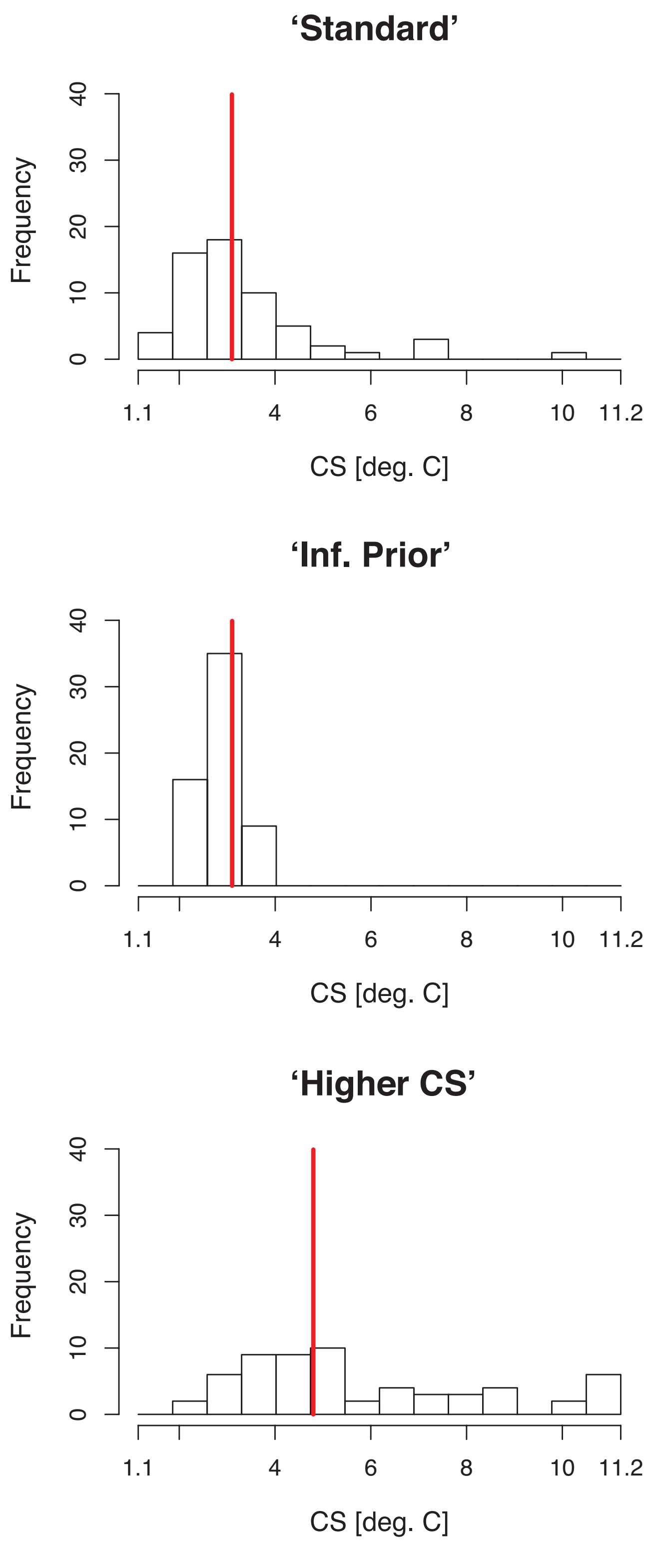

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