The impact of forcing efficacy on the equilibrium climate sensitivity

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Estimates of the Earth's equilibrium climate sensitivity (ECS) from 20th-century observations predict a lower ECS than estimates from climate models, paleoclimate data, and interannual variability. Here we show that estimates of ECS from 20th-century observations are sensitive to the assumed efficacy of aerosol and ozone forcing (efficacy for a forcer is the amount of warming per unit global average forcing divided by the warming per unit forcing from CO_2). Previous estimates of ECS based on 20th-century observations have assumed that the efficacy is unity, which in our study yields an ECS of 2.3 K (5%-95%-confidence range of 1.6-4.1 K), near the bottom of the IPCC's likely range of 1.5-4.5 K. Increasing the aerosol and ozone efficacy to 1.33 increases the ECS to 3.0 K (1.9-6.8 K), a value in excellent agreement with other estimates. Forcing efficacy therefore provides a way to bridge the gap between the different estimates of ECS.

1. Introduction

One of the most consequential but uncertain quantities in climate science is the equilibrium climate sensitivity (ECS), which is the equilibrium surface warming in response to a doubling of carbon dioxide. Estimates of the ECS can be obtained from observations of the warming over the 20th century [*Gregory et al.*, 2002; *Annan and Hargreaves*, 2006; *Aldrin et al.*, 2012; *Otto et al.*, 2013], climate models [*Soden and Held*, 2006; *Andrews et al.*, 2012; *Dalton and Shell*, 2013], paleoclimate data [*Hoffert and Covey*, 1992; *Crucifix*, 2006; *Lunt et al.*, 2010; *Schmittner et al.*, 2011], or from analysis of interannual variations [*Forster and Gregory*, 2006; *Dessler*, 2013].

These various estimates often do not agree. In particular, estimates of ECS from 20th-century observations generally imply most-likely values less than 2.5 K, lower than from the other data sources (although the uncertainties in all estimates are large enough to overlap). These low ECS estimates were one of the main reasons that the most recent IPCC report extended the bottom end of the likely ECS range from 2.0K to 1.5K [*Collins et al.*, 2013]. Understanding the differences in these estimates of ECS should therefore be a high priority.

2. Methodology and Datasets

The Earth's top-of-atmosphere (TOA) energy balance can be written:

$$N = F - \lambda \Delta T_{Sfc} \qquad (1)$$

N is the net energy imbalance for the Earth, F is the radiative forcing imposed upon the planet by, for example, an increase in greenhouse gases. $\lambda \Delta T_{Sfc}$ is the resulting surface temperature change and λ is the feedback factor, the change in TOA net flux per unit surface temperature change. We will solve Equation 1 for λ, from which an estimate of ECS can be obtained using the relation $ECS = \frac{F_{2xCO_2}}{\lambda}$, where F_{2xCO2} is the forcing from doubled CO_2 (3.7 W/m^2 [*Collins et al.*, 2013]).

In our calculations, we begin by integrating Equation 1 and then solving for λ:

$$\lambda = -\frac{\int N dt - \int F dt}{\int \Delta T_{sfc} dt} \quad (2)$$

with all integrals covering the period 1958-2010. The advantage of using an integral form is that it tends to reduce the impact of natural variability on the calculation [*Murphy et al.*, 2009]. For each term, we have a central value of the integral and an uncertainty, and we then use a Monte Carlo approach to estimate the probability distribution of λ. From this, we calculate the ECS range.

The term $\int N\, dt$, the time integral of the TOA net flux, is equal to the change in heat content of the climate system over the integral period. Because the heat content of the climate system is mainly stored in the ocean, we estimate this term from ocean heat content (OHC) estimates from the European Centre for Medium-Range Weather Forecasts' Ocean Reanalysis System 4 (ORAS4) [*Balmaseda et al.*, 2013]. The advantage of this data set is that it uses a reanalysis system to estimate the change in heat content for the entire ocean, including the deep ocean, which most observational data sets exclude. To account for the heating of non-ocean reservoirs (such as melting ice and land), we add an additional heat flux of 0.06 $\frac{W}{m^2}$ [*Hansen et al.*, 2011].

The ORAS4 contains five ensemble members, which sample plausible uncertainties in the wind forcing, observation coverage, and the deep ocean. We average them to come up with a single best-estimate value and use the standard deviation as the 1σ uncertainty in the Monte Carlo calculation.

Forcing comes from the IPCC's Fifth Assessment Report [Table 8.6 *Myhre et al.*, 2013], which provides forcing broken down by component. For aerosols, we use the effective radiative forcing, which allows tropospheric adjustment. In the Monte Carlo calculation, we assume a 1σ uncertainty in the integrated forcing of 20%, consistent with the IPCC's uncertainty estimate.

Monthly surface temperature anomalies come from the GISS Global Land-Ocean Index [*Hansen et al.*, 2010], HadCRUT4 [*Morice et al.*, 2012], and NCDC Global Index [*Smith et al.*, 2008]. The forcing time series is referenced to the late-19^{th} century, which means that the temperature anomaly time series must also be referenced to that same time. To do this, we offset each time series so that the 1880-1900 average is zero. We then integrate the three anomaly time series and average them to come up with a single best-estimate value and use the standard deviation as the 1σ uncertainty in the Monte Carlo calculation.

In the Monte Carlo calculation, 10^7 values of $\int N$, $\int F$, and $\int \Delta T_{sfc}$, are randomly sampled from the normal distributions described above and a value of λ is calculated for each one. From these 10^7 values of λ, an average value and confidence interval are calculated. ECS values are then calculated from the λ distribution.

3. Analysis

Using the data described above, we obtain an estimate for λ of 1.6 $\frac{W}{m^2K}$, with a 5-95% confidence interval of 0.9- 2.3$\frac{W}{m^2K}$; the PDF of λ is plotted in Fig. 1. This corresponds to an ECS of 2.3 K, with a 5-95% confidence interval of 1.6-4.1 K. In agreement with other recent calculations (summarized in Table 1), this estimate tends towards the bottom of the IPCC's sensitivity range.

It has long been expected that forcings with the same global average magnitude but different spatial patterns could evoke different responses in global surface temperature [*Hansen et al.*, 1997; 2005; *Shindell and Faluvegi*, 2009; *Shindell et al.*, 2010]. For example, forcing concentrated at high latitudes, which are less strongly restored by infrared radiation to space, will lead to more warming than well-mixed forcing agents. Certain forcing agents, particularly aerosols and tropospheric ozone, are indeed not uniformly distributed and impact the climate system differently than well-mixed constituents [*Shindell et al.*, 2003; *Feichter et al.*, 2004; *Chung and Seinfeld*, 2005; *Crook et al.*, 2011].

Different formalisms have been adopted in the literature to account for this process [e.g. *Hansen et al.*, 2005; *Winton et al.*, 2010; *Armour et al.*, 2013]. One is to account for the effect using a so-called forcing "efficacy" [*Hansen et al.*, 1997; 2005], which is the amount of warming per unit of global average forcing divided by the amount of warming per unit of forcing from carbon dioxide. Most calculations of ECS based on 20th-century observations assumed that the efficacy of different forcers is one, so this effect was ignored.

Recently, *Shindell* [2014] analyzed transient model simulations to show that the combined ozone and aerosol efficacy is about 1.5. At least some of the high efficacy of aerosols and ozone was due to nature of the transient runs he analyzed, but his analysis nevertheless clearly showed that, in the models at least, the efficacy of aerosol and ozone forcing was significantly greater than 1.0.

To test the impact of efficacy on the inferred λ and ECS in our calculations, we multiply the aerosol and ozone forcing time series by an efficacy factor in the calculation of the total forcing. We find that increasing the efficacy shifts the PDF of λ to lower values (Fig. 1), corresponding to increased climate sensitivity.

Using *Shindell's* [2014] estimate of efficacy of 1.5 decreases λ to 1.1 $\frac{W}{m^2K}$ (0.4-1.7 $\frac{W}{m^2K}$), corresponding to an ECS of 3.5 K (2.1-10.2 K). We can reasonably simulate the IPCC's climate sensitivity range using an efficacy of 1.33, which gives an ECS of 3.0 K (1.9-6.8 K).

Thus, an efficacy for aerosols and ozone of ≈1.33 would resolve the fundamental disagreement between estimates of climate sensitivity based on the 20th-century observational record and those based on climate models, the paleoclimate record, and interannual variations. It would also mean that the 20th-century observational record strongly supports the IPCC's canonical range. Clearly, better quantification of the forcing efficacy should be a high priority.

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Table 1. Estimates of λ and ECS based on 20th-century observations

Analysis	Central value of λ (W/m²/K)	5-95% confidence interval of λ (W/m²/K)	Central value of ECS (K)	5-95% confidence interval of ECS (K)
This analysis, efficacy = 1.0	1.6	0.9-2.3	2.3	1.6-4.1
This analysis, efficacy = 1.33	1.2	0.5-1.9	3.0	1.9-6.8
This analysis, efficacy = 1.5	1.1	0.4-1.8	3.5	2.1-10.2
Otto et al., 2013	1.8	N/A	1.9	0.9-5.0
Annan and Hargreaves, 2006	1.3	N/A	2.9	1.7-4.9
Aldrin et al., 2012	1.9	N/A	2.0	1.2-3.5
Skeie et al., 2014	N/A	N/A	1.8	0.9-3.2
Ring et al., 2012	N/A	N/A	~1.8	N/A

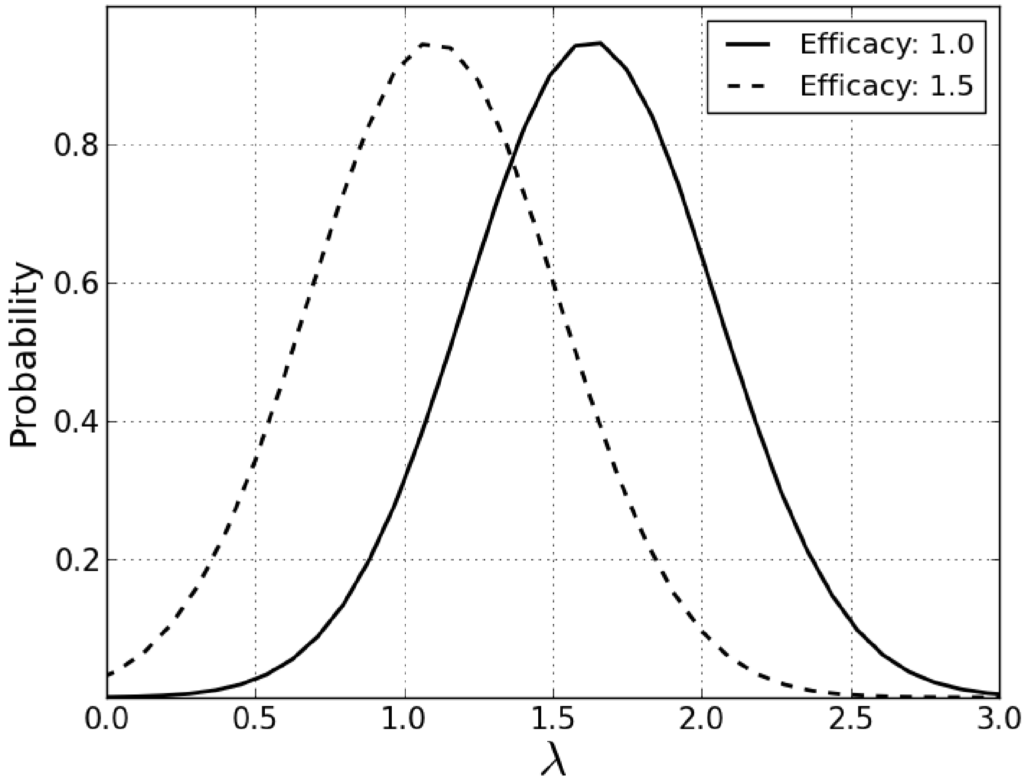

Figure 1. Probability distributions for λ (W/m^2/K) given two different efficacies, with units of fraction per W/m^2/K.