Supporting Information for "Narrowing Bounds on Earth's Climate Sensitivity"

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Introduction

This Supplemental Information describes in more detail the authors' reasoning as applied to the hypotheses for a surprisingly (very) high or low Equilibrium Climate Sensitivity, ECS. It does so by elaborating on studies based primarily on interpretations of the instrumental record, palaeoclimate studies, and physical understanding, including present day observations designed to constraint specific processes relevant to feedback processes. This analysis helps rationalize the choice of likelihoods assigned to different lines of evidence in the framework of the Bayesian inference. Further details and sensitivities within this inferential framework are also described. Note that in some cases citations are less exhaustive then they would be for a stand-alone supplement (which would appear as part of a more formal study or assessment) as journal policy does not allow articles to be cited in the supporting information if they are not cited in the main article.

S1: Instrumental record.

A large number of studies [*Stocker et al.*, 2013] have attempted to infer the ECS by fitting simple models to different aspects of the instrumental record. The models are characterized as simple because they assume that temperature anomalies can be linearly related to radiation anomalies through a single parameter, often called the climate feedback parameter and denoted by λ. By convention a negative net feedback implies a stable climate so that the temperature change, ΔT, after the system returns to stationarity in response to a radiative forcing, F, is given as

$$\Delta T = -\frac{F}{\lambda} \tag{S1}$$

For sufficiently small perturbations about an arbitrary stationary reference state, λ (with units of $\mathrm{W\,m^{-2}\,K^{-1}}$) can be thought of as the radiative response to warming. The particular value of λ for the special case where the starting state of the model is taken to be the pre-industrial climate state, and F is the forcing that arises from a doubling of atmospheric CO_2, this equation can be used to define the ECS as

$$\mathrm{ECS} = -\frac{F_{2\times}}{\lambda_{2\times}}. \tag{S2}$$

So this implies that the ECS is determined by a particular value of λ, namely $\lambda_{2\times}$, which arises when the forcing is a doubling of CO_2 and the stationary starting state is taken to be the state of the climate system in the preindustrial period. In assuming that the radiative response to an arbitrary forcing, λ, is constant, simple models do not distinguish between λ and $\lambda_{2\times}$. In contrast to many simple models, comprehensive models are defined in part by the fact that their value of λ is an emergent property of the model that arises through the competition of different processes, and as such is not directly specified or fitted, and can vary with the state of the climate system.

By matching the state of the simple model to available data it is possible to derive estimates for the model parameters, and by inference the ECS. Early studies adopting this approach suggested that the instrumental record did not strongly constrain ECS [*Knutti and Hegerl*, 2008; *Collins et al.*, 2013]. More recent studies, which benefit from methodological advances and more data, conclude that the instrumental temperature record confidently rule out high (greater than about 2.8 K) values of ECS, Table S1.

This conclusion is, however, subject to some important caveats. The first is that the upper (95 %) confidence bound is sensitive to the end period chosen for the analysis as well as assumptions about the aerosol forcing. Choosing a longer end period as in the original *Lewis and Curry* [2014] and *Otto et al.* [2013] studies increases the upper bound of the 95 % confidence interval to 5.4 K and 5.0 K respectively. Studies which continue to allow for a very strong (more negative than $-1\,\mathrm{W\,m^{-}2}$) aerosol forcing yield a 95 % confidence bound close to 4 K, studies that no longer accommodate such a large aerosol forcing (TableS1), give a 95 % bound nearer 2.5 K.

A second caveat emerges from a perfect model study which tests the ability of the simple model approach to reproduce the ECS of a more comprehensive model using an ensemble of historical simulations covering a range of decadal variability realizations [*Huber et al.*, 2014]. The estimates of ECS using the simple model assumptions were shown not only to underestimate the actual ECS on average, but also to be sensitive to the particular realization of variability in the historical period, varying by up to ± 1.6 K relative to the ensemble mean prediction. This finding raises the possibility that simple model estimates of ECS could be biased because of a dependence on the particular realization of unforced variability which happened to occur in the historical period, but does not influence the actual ECS.

More recent studies with comprehensive climate models have made these caveats more precise and call into question the idea that λ can be assumed to be constant. A number of studies argue for a "pattern effect", whereby λ depends on the pattern of the surface temperature response (or the state of the model) in a way that the interpretation of the instrumental temperature record based on simple models does not capture [e.g., *Senior and Mitchell*, 2000; *Geoffroy et al.*, 2013; *Armour et al.*, 2013; *Gregory et al.*, 2015; *Knutti and Rugenstein*, 2015; *Gregory and Andrews*, 2016]. In the great majority of comprehensive models, this pattern effect would cause estimates of ECS using a constant λ to be biased low, for reasons that are partially understood [*Senior and Mitchell*, 2000; *Geoffroy et al.*, 2013; *Armour et al.*, 2013; *Gregory et al.*, 2015]. Most studies using comprehensive models suggest a modest pattern effect between initial and long term warming in the carbon dioxide quadrupling scenarios, leading to a 20-30 % under-estimate of ECS if not accounted for [*Geoffroy et al.*, 2013; *Armour et al.*, 2013; *Knutti and Rugenstein*, 2015; *Andrews et al.*, 2015].

Correcting the simple model interpretations of the instrumental record by allowing for a 33 % pattern effect would imply that the studies cited in Table S1 can, with some (here the eighty-third percentile) confidence, rule out values of ECS greater than about 2.4 K to 3.7 K, depending on the study. We adopt a more conservative statement, and assert that an ECS greater than 4 K becomes difficult to reconcile with the instrumental temperature record. Some recent work suggests that even such a large correction to the upper bound (from 2.8 K to 4.0 K) may still insufficiently account for pattern effects [*Gregory and*

Andrews, 2016], thereby further undermining the ability of the instrumental record to refute the story line for a very high ECS.

S2: Last Glacial Maximum, LGM.

Simple Models have been applied to studies of the last glacial maximum (LGM) in a similar way as has been done for the historical temperature record [*Rohling et al.*, 2012; *Knutti and Hegerl*, 2008]. These provide estimates of ECS whose one sigma range varies from 1.7 K to 4.5 K. Although most of these studies also apply simple models whose parameter sensitivities can be fully sampled, the question as to whether the proxy record for the LGM constrains the climate sensitivity of more comprehensive models has also been explored [*Hargreaves et al.*, 2012; *Schmidt et al.*, 2014]. Comprehensive modeling studies carried out as part of the palaeoclimate modelling intercomparison project (PMIP) show a reasonably strong relationship between tropical sea-surface temperature changes in the LGM relative to the present (denoted δ_T) and the ECS [*Hargreaves et al.*, 2012]. A relationship between δ_T and ECS is evident also in studies employing simpler models [*Schmittner et al.*, 2011], and makes physical sense. Nonetheless, a recent study incorporating models which have begun to incorporate a more diverse treatment of uncertain physical processes has called this relationship into question [*Hopcroft and Valdes*, 2015].

Estimates of δ_T vary in the literature. The Multi-proxy Approach for the Reconstruction of the Glacial Ocean Surface [MARGO, *Waelbroeck et al.*, 2009] project was designed to address many previous shortcomings in earlier reconstructions of tropical SSTs during the LGM. Using estimates of δ_T to better constrain estimates of ECS, a confidence interval (5 % to 95 %) of 1 K to 4.2 K has been derived based on analysis of comprehensive models and 1.4 K to 2.8 K from a simple model whose parameters could be more formally constrained [*Schmittner et al.*, 2011]. Studies of the LGM with both comprehensive and simple models may be subject to the pattern effect discussed above in the context of interpretations of the instrumental record, and are also influenced by any possible biases in the reconstructions of tropical SSTs. Recently the MARGO reconstruction has been re-evaluated using SST patterns derived from comprehensive modeling of the LGM, resulting in a larger δ_T [*Annan and Hargreaves*, 2015]. When applied to the analysis of comprehensive models this shifts the ECS confidence interval by about 0.5 K (1.6 K to 4.5 K). Sensitivity tests suggest that a similar change can be expected for earlier studies which would otherwise fail to constrain surprisingly low values of ECS [*Schmittner et al.*, 2011]. The idea that MARGO estimates of δ_T are biased low, and hence ECS estimates constrained by the MARGO data are also biased low has received further support from recent work using clustered isotopes to study changes in the tropical snow-line during the LGM [*Tripati et al.*, 2014].

S3: Eocene and late Palaeocene Thermal Maximum.

Large and positive values of δ_T occurred in the more distant past. Several epochs through the late Phanerozoic have been used to constrain ECS [see *Rohling et al.*, 2012, for a review], most prominently the late Palaeocene and early Eocene during which δ_T was at least 10 K, and a brief “hyper-thermal” warming spike at the boundary between these periods known as the Palaeocene-Eocene Thermal Maximum (PETM) during which δ_T shot up by another 5 K. Temperatures are not known exactly but are supported by incontrovertible evidence such as crocodilian fossils in the Arctic and tropical plants growing in (presently) cold continental interiors at high latitudes.

The Paleocene-Eocene background warmth can be attributed to the high levels of CO_2 inferred from proxy evidence and calculated based on the more active plate tectonics at the time [*Berner and Kothavala*, 2001]. CO_2 amounts are highly uncertain however (in contrast to the LGM case) and even less is known about other greenhouse gases, such that radiative forcings are not well known. Another problem is that climate feedbacks and forcings are each expected to vary under large climate changes, such that one cannot simply take a ratio of δ_T to forcing to yield ECS [*Rohling et al.*, 2012]. Nonetheless such warm climates appear to require a robust minimum ECS of at least 1.5 K, given reasonable assumptions about the carbon cycle and proxy evidence for CO_2 [*Royer et al.*, 2007; *Bijl et al.*, 2010; *Covey et al.*, 1996; *Rohling et al.*, 2012]. More recent investigations suggest a much more elevated lower bound of around 4 K on present-day ECS based on evidence from the Pliocene, late Eocene and early Oligocene periods [*Rohling et al.*, 2012].

The PETM event was caused by a rapid carbon release into the atmosphere as shown by carbon isotopic changes. Proxy greenhouse gas estimates imply ECS of 3.5 K-6.0 K [*Pagani et al.*, 2006; *Rohling et al.*, 2012], but this depends on the amount of greenhouse gases involved, which is sensitive to how records are interpreted and may be more than previously thought [*Alexander et al.*, 2015]. Uncertainty in background CO_2 is not quite as important, since it has a compensating effect on ECS estimated from the background warmth vs. from the PETM: the former is higher if there was less background CO_2, while the latter is higher if there was more (due to the logarithmic dependence of radiative forcing on CO_2 amount).

Clearly the evidence from hothouse climates as a whole does not present any real problem for a weak radiative response to warming in that era, consistent with a high ECS of

4.5 K or more, but at face value, rules out a very low ECS. Given the wide range of time periods and sources of proxy evidence that have been explored, to permit a very low ECS would seem to require a systematic (and substantial) bias having affected all studies. The main candidates that we see would be: i) increases in methane or other greenhouse gases systematically coinciding with those of CO_2, ii) systematic underestimation of past CO_2 changes, or iii) a large (factor of two or more) difference between λ in warmer climates and $\lambda_{2\times}$. The first is problematic because it would imply a positive methane feedback that would presumably also apply today. The second would require that multiple lines of evidence on CO_2 (several proxies and carbon-cycle modeling calculations of CO_2) each be incorrect. The third appears likely to some extent, and should be more actively explored to see how large the difference could be. To the extent that these possibilities can be eliminated or their effect quantified, hothouse climate changes may prove useful in establishing a lower bound on ECS, but given the very large differences in the climate system, and the difficulty in interpreting the evidence from such a distant past, caution should be exercised in attributing too much weight to this element of the story line.

S4: Physical understanding of climate feedbacks.

Climate feedbacks characterize how responsive the net outgoing radiation at the top of the atmosphere is to a global warming of the Earth's surface. The feedbacks associated with the radiative impact of clouds changes with warming are referred to as cloud feedbacks, while the other ones (associated with changes in surface and atmospheric temperatures, humidity, snow and sea-ice) are referred to as clear-sky (or non-cloud) feedbacks.

Clear-sky feedbacks are physically well understood and fairly robust across models: they arise from the temperature dependence of infrared emission (Stefan-Boltzmann law), from water vapor changes with warming that closely follow the thermodynamic relationship of Clausius-Clapeyron (i.e. that correspond to a nearly unchanged relative humidity as climate is warming), and from the enhanced melting of snow and sea-ice as the surface temperature rises. The sum of clear-sky feedbacks (including the Planck response) diagnosed from comprehensive models is $-1.8 \pm 0.2\,\mathrm{W\,m^{-2}K^{-1}}$ for long-term anthropogenic climate change [*Vial et al.*, 2013; *Dessler*, 2013]. The nature and amplitude of these feedbacks are supported by a large and growing body of evidence, including physical reasoning tested in a hierarchy of numerical models and in observations [*Sherwood et al.*, 2010; *Stevens and Bony*, 2013] and observational tests of the model feedbacks on a variety of time scales [*Boucher et al.*, 2013; *Dessler*, 2013; *Zhou et al.*, 2015]. Given these feedbacks, an ECS lower than 2 K seems very unlikely, unless clouds provide a substantially negative feedback. On the other hand, positive cloud feedbacks have the potential to produce substantially higher ECS estimates.

A quantitative assessment of cloud feedbacks remains challenging. Nevertheless, while long considered as a mystery of climate science, the physics of cloud feedbacks is now becoming less enigmatic. Recent analyses using a wide hierarchy of models, ranging from process to comprehensive models, have pointed out a number of positive feedback mechanisms. One relates to the tendency of upper-tropospheric clouds to rise as the climate warms while maintaining roughly the same temperature at cloud-top. This mechanism, which is well explained by physical reasoning [*Hartmann and Larson*, 2002], tested by high-resolution process models [*Kuang and Hartmann*, 2007] and supported by observations [*Zelinka and Hartmann*, 2011], is considered as robust and responsible for a positive ($\approx 0.2\,\mathrm{W\,m^{-2}K^{-1}}$) feedback [*Zelinka et al.*, 2016].

Another positive feedback arises from the reduction of the low-cloud amount as the climate warms. A number of explanations have been proposed to explain this behavior, including reductions in moisture availability from surface evaporation [*Rieck et al.*, 2012; *Webb and Lock*, 2012], boundary layer drying by enhanced mixing with dry air from the free troposphere [e.g., *Brient and Bony*, 2013; *Zhang et al.*, 2013; *Sherwood et al.*, 2014; *Webb et al.*, 2015], and increased downward longwave emission from the free troposphere suppressing boundary layer turbulent mixing [*Bretherton et al.*, 2013]. Some of these arise from studies with very high resolution process models, which provide additional support for positive cloud feedbacks from low clouds [*Bretherton*, 2015]. However, the strength of the low-cloud feedback depends on the relative importance of antagonist influences [*Rieck et al.*, 2012; *Zhang et al.*, 2013; *Brient et al.*, 2015], and in models it is sensitive to the representation of turbulent and convective processes [*Gettelman et al.*, 2012; *Qu et al.*, 2013; *Zhao*, 2014; *Webb et al.*, 2015]. Consistently, its estimate varies greatly across models (ranging from $-0.1\,\mathrm{W\,m^{-2}\,K^{-1}}$ to $+0.6\,\mathrm{W\,m^{-2}\,K^{-1}}$), and it remains the primary source of uncertainty in ECS estimates [*Boucher et al.*, 2013].

A negative cloud feedback mechanism has been pointed out at high latitudes [*Zelinka et al.*, 2013], where warming causes clouds to become more reflective owing to ice changing to liquid [*Kay et al.*, 2014] and maybe additional processes [*Betts and Harshvardhan*, 1987]. Although this feedback is presumably too pronounced in climate models [*Gordon and Klein*, 2014], it is much too weak to compensate for the other positive cloud feedbacks at the global scale. It has been argued that an Iris Effect [i.e. a reduction of the upper-level cloud amount as the climate warms, e.g., *Lindzen et al.*, 2001] could produce a negative feedback. However, although an Iris effect is possible [*Bony et al.*, 2016] and even present in many models, both observations [*Zelinka and Hartmann*, 2011] and comprehensive models [*Mauritsen and Stevens*, 2015] suggest that its ability to produce a substantial negative feedback is largely hindered by the strong compensation between the infrared and solar effects of changes in high-cloud amount.

The evidence for robust positive feedbacks from clear-sky processes, low-level clouds and upper-level clouds, plus the lack of evidence for substantially negative cloud feedbacks, constitute strong refutation arguments for an ECS less than 1.5 K, and even calls into question values of ECS less than 1.5 K. Physical understanding is however not sufficiently advanced to firmly constrain the upper bound of ECS estimates, largely because of uncertainties in the magnitude of the low-cloud feedback. If some observational constraints support ECS values in the upper range of model estimates [*Sherwood et al.*, 2014], other studies question the implications for the strength of the low-cloud feedback of model biases in the simulation of present-day low-level clouds [*Nuijens et al.*, 2015; *Brient et al.*, 2015]. A better quantification of the low-cloud feedback would greatly help assess the plausibility of a high or very high ECS.

S5: Bayesian inference.

For the section on Bayesian inference the prior arises from our most basic understanding of atmospheric physics, namely of how the atmosphere would respond to forcing. [*Stevens and Bony*, 2013]. It describes how the atmosphere would respond if the troposphere deepened with temperature consistent with the radiative definition of the tropopause (Fixed Anvil Temperature Hypothesis, or FAT), with relative humidity constant and no changes in clouds, except that their vertical extent is extended or contracted as the troposphere warms or cools, following FAT, and surface albedo increasing as ice retreats with warming. In contrast to what was adopted by *Stevens and Bony* [2013], the feedback associated with clouds rising in a deepening troposphere is reduced in magnitude from $0.4\,\mathrm{W\,m^{-2}\,K^{-1}}$ to $0.2\,\mathrm{W\,m^{-2}\,K^{-1}}$ following more recent work to estimate this effect (Mark Zelinka personal communication, 2016). This leads to the prior being centered around a somewhat smaller value of ECS (2.2 K versus 2.7 K) as compared to what was suggested by Stevens and Bony. The uncertainty in the forcing, F, and feedback, λ, used to generate the prior are large, resulting in the prior having the form

$$\mathrm{ECS} = -\frac{F + \sigma_f}{\lambda + \sigma_\lambda} \tag{S3}$$

where σ_f is a gaussian distributed random variable with standard deviation of $0.2F$. Likewise σ_λ is also a gaussian distributed random variable with standard deviation of 0.5λ. For F and λ we adopt $3.7\,\mathrm{W\,m^{-2}}$ and $-1.6\,\mathrm{W\,m^{-2}\,K^{-1}}$ ($\lambda_{\mathrm{clr}} + \lambda_{\mathrm{FAT}} = -1.8 + 0.2\,\mathrm{W\,m^{-2}\,K^{-1}}$) respectively. The prior is constrained to only sample ECS values between 0 K and 10 K[1] by renormalizing the resultant conditional distribution $p(\chi|\chi > 0)$

There is an extensive literature on the choice of priors, and the issues are reviewed by *Annan* [2015]. We believe our choice of prior is reasonable, and not unduly influenced by the lines of evidence used to construct the posteriori distribution. Assuming a larger uncertainty in the forcing and the feedback, whereby $\sigma_\lambda = 0.75\lambda$ and $\sigma_F = 0.25F$ produces a similar result as compared to Fig. 2 of the manuscript, but for different values of σ (Fig. S1). It illustrates, that inferences drawn from the likelihood of the evidence are not especially sensitive to the details of the prior.

The exact form for the error function that was adopted in creating the likelihoods is:

$$P(e_j|\chi) = \frac{(1-2\varepsilon_j)\ \mathrm{erf}\,(2\chi - 2\chi_j) + 1}{2}, \quad \text{where} \quad 0 \le \varepsilon_j \le 0.5 \tag{S4}$$

where erf denotes the standardized error function. Physically one can think of this as a way to modify the null-hypothesis, as $\varepsilon_j = 0.5$ leads to all values of ECS being equally likely and thus does not modify the prior. The parameters for Eq. (S4) are provided in Table S2. The parameter ε_j is equal to the likelihood of misleading evidence, α_j, for the conditions related to the low ECS. For the high ECS, the likelihood of misleading evidence is given by $1 - \varepsilon_j$.

The parameter ε_j weights the marginal value of the evidence in refuting an argument for a value of the ECS exceeding a given bound. Because the form we adopted for the likelihood is a symmetric around χ_j, a 25 % likelihood of evidence being misleading for values of $\chi \gg \chi_j$ is balanced by a 75 % likelihood that the evidence is compatible with a value of $\chi \ll \chi_j$. And because the weight of the evidence in shaping the the expectation depends on the differential likelihood, this formulation ends up being a weaker statement about the strength of the evidence than might otherwise intuited. The use of the error function provides a smooth transition between the likelihoods shaped by the marginal value of the evidence. Experiments with piecewise linear functions give similar results.

Different elements of the story line for a very high or very low ECS were quantitatively explored in §1 through §4 above and these were used to construct values of χ_j and ε_j in Table S2. Certainly these choices are subject to discussion, with “pattern effects” arising as a common thread adding uncertainty in the interpretation of many of the lines of evidence, especially for the very high ECS story line. To show how our framework can address this uncertainty we explore how alternative interpretations of the evidence would effect the posterior distribution that arises from this analysis.

In one sensitivity study we made the transition region about the threshold ECS χ_j twice as large, and increasing the value of χ_j for each of the lines of evidence for conditions for the high ECS storyline by 0.5 K, for instance to reflect concerns that pattern effects are not sufficiently accounted for when interpreting past records [*Gregory and Andrews*, 2016; *Andrews*, 2014]. This slightly changes the 5th and 95th percentiles of the distribution, to 1.5 K and 4.5 K respectively, but the median remains unchanged (Fig. S2, also Table S3). To estimate how a better understanding of the sign of cloud feedbacks might influence the posterior distribution we reduced ε_j for this condition of the very low ECS story-line to 0.15 and increased χ_j to 2.0 K. This increased the value of the 5th percentile from 1.6 K to 1.8 K. Without this process constraint on the low-end ECS whatsoever the 5th percentile value remains quite low, at 1.4 K. Finally, we explored the influence of our interpretation of the instrumental record on the likelihood of high-end sensitivities. Here we modified $\varepsilon_{(i)}$ to 0.6, giving it as little weight as we give to understanding of feedback processes. This increases the value of the 95th percentile by 15 %, from 4.1 K to 4.7 K. Given that the 95th percentile value of the prior is 6.1 K, this suggests that even weak statements about our understanding of the past record and its relation to the present can provide useful constraints on the high-end sensitivities.

Notes

1. Clarification to how the bounds on the prior was set was added after publication

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Study	ECS 17-83 % CI (K)	5-95 % CI (K)
Aldrin et al. [2012]	1.2–2.0	1.1–2.6
Otto et al. [2013]	1.5–2.8	1.2–3.9
Lewis and Curry [2014]	1.3–2.5	1.1–4.1
Lewis and Curry [2014], revised	1.2–1.8	1.1–2.2

Table S1. ECS estimates inferred by simple models constrained by the instrumental record. The revised version of the Lewis and Curry estimate employs the aerosol-forcing bounds of *Stevens* [2015].

	Low ECS			High ECS		
Condition	(ii)	(iii)	(iv)	(i)	(ii)	(iii)
ε_j	0.25	0.35	0.20	0.75	0.65	0.60
χ_j [K]	1.50	1.50	2.00	4.00	4.50	4.50

Table S2. Parameters for likelihood functions for applicable conditions of a low (< 1.5 K) and high (> 4.5 K) ECS.

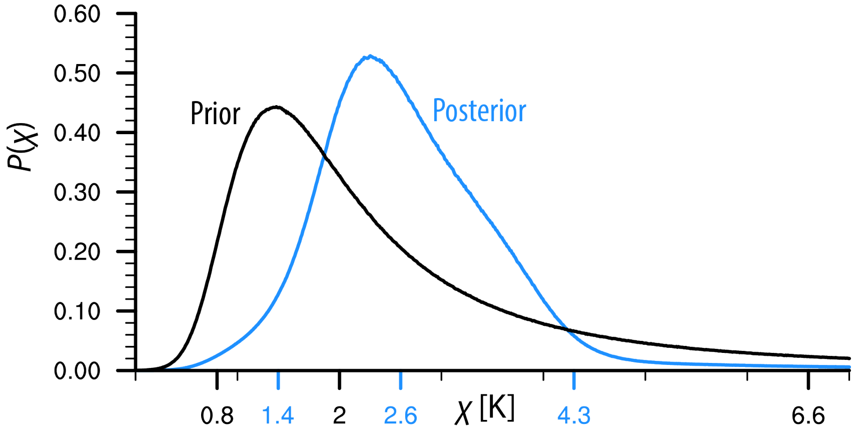

Figure S1. The prior (black) and posterior (blue) distributions with 5, 50 and 95 percentiles of the respective distributions indicated by major tick marks for the case of a broader prior ($\sigma_\lambda = 0.75\lambda$ and $\sigma_F = 0.25F$.)

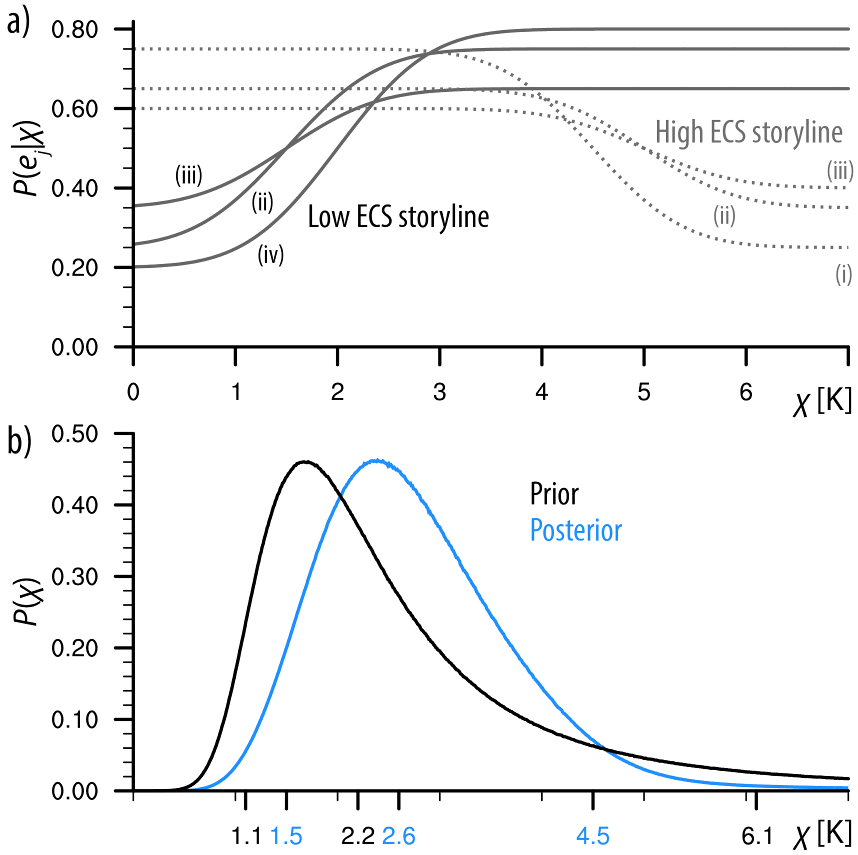

Figure S2. For comparison with Fig. 1. A case where to account for a larger than anticipated pattern effect, the values of χ_j are increased by 0.5 K for all the lines of evidence associated with the storyline for a very high ECS and the uncertainty in all values of χ_j is increased by a factor of 2.

Experiment	$P(\chi < 1.5)$	$P(\chi < 2.0)$	$P(\chi > 4.0)$	$P(\chi > 4.5)$	$P(\chi > 6.0)$
Prior	0.19	0.41	0.15	0.11	0.05
Broad Prior	0.31	0.50	0.16	0.13	0.07
Posterior P	0.03	0.18	0.06	0.03	0.01
Posterior P1	0.06	0.21	0.11	0.05	0.01
Posterior P2	0.21	0.46	0.06	0.04	0.02
Posterior P3	0.03	0.17	0.10	0.06	0.02
Posterior BP	0.06	0.21	0.08	0.04	0.02

Table S3. Probability for the ECS, χ, to lie in a specific interval. Shown are the distributions for the priors and posterior for four experiments: Example in manuscript (P); case for χ_j increased by 0.5 K for all lines of evidence in the high-ECS storyline and uncertainty in χ_j increased by a factor of two for all lines of evidence (P1); case where only the line of evidence from the instrumental record is adopted (P2); case where the historical evidence is assumed to be much weaker, so that $\alpha_j = 0.4$ instead of 0.25, (P3); same as case P but for the broader prior (BP).