Lewis (2022) Objectively combining climate sensitivity evidence – Detailed Summary

A paper in Climate Dynamics contesting the influential WCRP assessment of climate sensitivity

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Introduction

In 2015 over thirty experts attended a week-long workshop in Ringberg Castle to assess gaps in understanding of Earth's climate sensitivities. The workshop was organised under the auspices of the World Climate Research Programme (WCRP) Grand Science Challenge on Clouds, Circulation and Climate Sensitivity. Critically, WCRP-supported research provides the climate science that underpins the United Nations Framework Convention on Climate Change. This WCRP-initiated assessment process culminated in the publication in 2020 of a 92-page paper "An Assessment of Earth's Climate Sensitivity Using Multiple Lines of Evidence" by Steven Sherwood and 24 co-authors (Sherwood20). This paper has been extremely influential, including in informing the assessment of equilibrium climate sensitivity (ECS) in the 2021 IPCC Sixth Assessment Scientific Report (AR6); it was cited over twenty times in the relevant AR6 chapter.

I attended the 2015 Ringberg workshop and have since published papers concerning how to combine multiple lines of evidence regarding climate sensitivity using an Objective Bayesian statistical approach. Disappointingly, Sherwood20 (which I had no involvement with) instead used the common Subjective Bayesian method that, while simpler, my research had showed may result in unrealistic estimates and uncertainty ranges. I therefore decided to replicate Sherwood20, to implement an Objective Bayesian approach, and also to review Sherwood20's choice of probabilistic estimates for the input assumptions used ("data-variables"). In doing so I discovered another, more fundamental and potentially more serious, statistical problem in Sherwood20, as well as important conceptual errors and inconsistencies. I also found that after fixing these problems and also substituting values derived from more recent sources of evidence, including AR6, for certain of the data-variable estimates used by Sherwood20, the resulting estimate of climate sensitivity fell substantially.

A paper "Objectively combining climate sensitivity evidence" covering my work on this project has now been published by Climate Dynamics, (Lewis22). Its Abstract reads:

> Recent assessments of climate sensitivity per doubling of atmospheric CO_2 concentration have combined likelihoods derived from multiple lines of evidence. These assessments were very influential in the Intergovernmental Panel on Climate Change Sixth Assessment Report (AR6) assessment of equilibrium climate sensitivity, the *likely* range lower limit of which was raised to 2.5°C (from 1.5°C previously). This study evaluates the methodology of and results from a particularly influential assessment of climate sensitivity that combined multiple lines of evidence, Sherwood et al. (2020). That assessment used a subjective Bayesian statistical method, with an investigator-selected prior distribution. This study estimates climate sensitivity using an Objective Bayesian method with computed, mathematical priors, since subjective Bayesian methods may produce uncertainty ranges that poorly match confidence intervals. Identical model equations and, initially, identical input values to those in Sherwood et al. are used. This study corrects Sherwood et al.'s likelihood estimation, producing estimates from three methods that agree closely with each other, but differ from those that they derived. Finally, the selection of input values is revisited, where appropriate adopting values

based on more recent evidence or that otherwise appear better justified. The resulting estimates of long-term climate sensitivity are much lower and better constrained (median 2.16°C, 17−83% range 1.75−2.7°C, 5−95% range 1.55−3.2°C) than in Sherwood et al. and in AR6 (central value 3°C, *very likely* range 2.0−5.0°C). This sensitivity to the assumptions employed implies that climate sensitivity remains difficult to ascertain, and that values between 1.5°C and 2°C are quite plausible.

What Sherwood20 did

ECS, a theoretical measure of climate sensitivity, represents the change in global surface temperature in response to a doubling of atmospheric CO_2 concentration, after the ocean reaches equilibrium. Sherwood20 actually estimated a proxy for ECS, termed *S*, that corresponds to estimating ECS by projecting the relationship between warming and the Earth's radiative imbalance with space over the 150 years following a hypothetical abrupt quadrupling of preindustrial CO_2 concentration. That relationship is estimated by linear regression, and projected to the point at which the Earth's radiative imbalance returns to its equilibrium value of zero. The warming at that point is rescaled, so as to correspond to the effect of doubling CO_2.

Simulations by global climate models (GCMs) of such a scenario suggest that *S* is slightly lower than ECS, due to the climate feedback strength – the strength of the relationship between net outgoing radiation and surface temperature – applicable to an imposed radiative change (forcing) declining over time. However, *S* is more relevant than ECS to estimating warming over the next century or two.

Sherwood20 combined evidence based on several different lines of evidence: process understanding (feedback analysis), the historical period (instrumental) record, and paleoclimate data from both warm and cold periods. This is a strong scientific approach, in that it utilizes a broad base of evidence and avoids direct dependence on GCM climate sensitivities. Such an approach should be able to provide more precise and reliable estimation of climate sensitivity than that in previous IPCC assessment reports.

The cold paleoclimate evidence concerned changes between the last glacial maximum (LGM) and preindustrial periods. Sherwood20 analyzed paleoclimate data from two warm periods, the mid-Pliocene warm period (mPWP) and the more distant Paleocene-Eocene Thermal Maximum (PETM), but did not use PETM data in their main results. Thus, Sherwood20 used three main lines of evidence (Process, Historical and Paleoclimate), with LGM and mPWP evidence being combined to represent Paleoclimate evidence.

Sherwood20 also estimate a sensitivity (S_{hist}) from historical data alone, on the standard energy balance basis used in most past assessments of ECS from historical data. That basis assumes climate feedback strength applicable to ECS remains the same as it was over the historical period. When estimating *S* from historical data, Sherwood20 adjust that energy balance based climate feedback estimate to convert it into an estimate of the long-term climate feedback that they require for estimating *S*.

Traditionally global mean surface temperature (GMST), which blends land near-surface air temperature with sea surface temperature over the ocean, has been used when estimating climate sensitivity from historical warming. However, Sherwood20 define ECS, *S* and S_{hist} in terms of the change in global mean near-surface air temperature (GMAT), which in GCMs changes more than GMST.

Sherwood20 judged errors in estimates of variables ('data-variables'), such as temperature changes, relating climate sensitivity to each of the lines of evidence used, to be largely independent, save for data-variables that were common between them, notably the effective radiative forcing (ERF)[1] from a doubling of preindustrial CO_2 concentration ($F_{2\times CO2}$). This statistical independence assumption, which appears reasonable, greatly simplifies combining the different lines of evidence regarding *S*.

Sherwood20 represented the information about *S* provided by each line of evidence by its likelihood function, as is standard. The likelihood function represents, for each value of *S*, the estimated probability of the values of the uncertain data variables representing the evidence that are consistent with that value of *S*, given the estimated probability distributions of those variables.

Two main problems with the statistical methods used by Sherwood20

First, Sherwood20 employed a 'Subjective Bayesian' statistical approach to convert the estimated likelihoods into a probabilistic estimate for *S*, using an 'updating' method to combine evidence regarding *S*, rather than using more reliable 'Objective Bayesian' methods: see Appendix A. In the past, climate scientists using Subjective Bayesian methods to estimate climate sensitivity often selected an inappropriate 'prior distribution' to represent pre-existing knowledge about it, resulting in substantially biased estimates. Moreover, I had previously shown (Lewis 2018) that Bayesian updating could be expected to produce a biased estimate for climate sensitivity, even if the selected prior distribution resulted in accurate estimation when used for the first line of evidence alone.

Secondly, the method Sherwood20 used to estimate likelihoods, other than for Process evidence (for which the likelihood can be calculated directly), was unsound. Their method produced substantially inaccurate estimates for Historical likelihood (at *S* and S_{hist} values above the likelihood maximum) and PETM likelihood (at all *S* values): see Appendix B. Their estimate for mPWP likelihood was also somewhat inaccurate.

In Lewis22, I replicate Sherwood20, but using accurate likelihood estimation methods. I employ an 'Objective Bayesian' statistical approach, not involving updating, using a mathematical "Jeffreys' prior" that is known to produce estimates with uncertainty limits agreeing as closely as is possible with confidence bounds, which are usually considered the 'gold standard' measure. As it happens, neither the use of a Subjective Bayesian method nor the flawed likelihood estimation led to significant bias in Sherwood20's estimate of *S* when all lines of evidence were combined. Nevertheless, for there to be confidence in the results obtained, sound statistical methods that can be expected to produce reliable parameter estimation must be used.

Updates to Sherwood20's data-variable estimates

My paper then goes on to revisit Sherwood20's probabilistic data-variable estimates, and to revise some of them, primarily to reflect more recent evidence and to correct deficiencies in Sherwood20's treatment of $F_{2\times CO2}$. These revisions, while limited, have a major effect. They reduce by one-third, from 3.23°C to 2.16°C, the median estimate of *S* given by the combined evidence, using Jeffreys' priors and warm Paleoclimate evidence from the mPWP in both cases. The 83% and 95% uncertainty bounds reduce respectively from 4.1°C to 2.7°C and from 5.05°C to 3.2°C.

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[1] ERF is a measure of the change in the Earth's radiative imbalance at the top of the atmosphere, measured downwards, (ΔN) resulting from a change in atmospheric constituents or other driver of climate change, once the atmosphere has adjusted to the effects of that change, in the absence of any change in surface temperature.

The changes to the posterior PDFs for *S* based on each main line of evidence and for all of them combined are shown in Figure 1. Consistency between median *S* values from different lines of evidence is much improved when based on the revised assumptions.

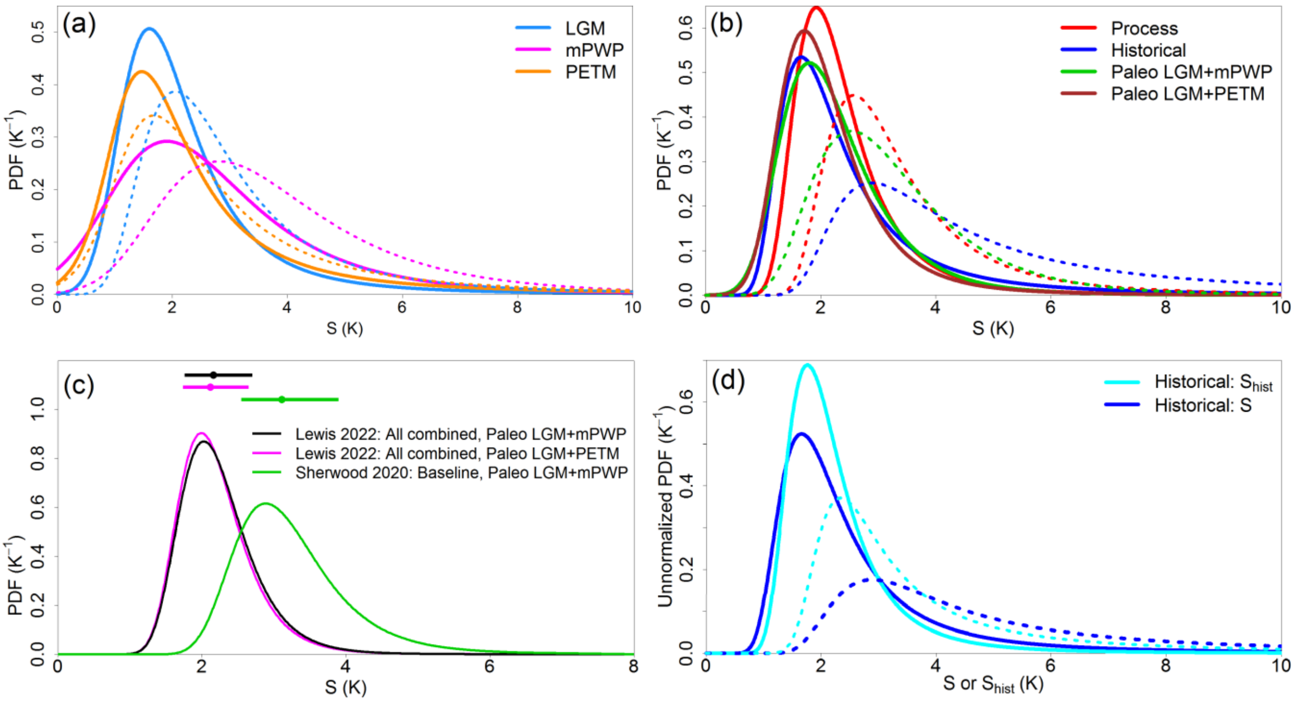

Fig.1 Posterior Probability Density Functions for *S* based on the revised and original data-variable assumptions. Save for the Sherwood20 green line in panel (c), correctly calculated likelihoods and the Objective Bayesian method were used, with solid lines when using the revised assumptions and dotted lines when using the original assumptions. In panels (a), (b) and (c), the PDFs have all been normalized to unit probability over 0–20 K. (a) PDFs for *S* from Paleoclimate LGM, mPWP and PETM evidence separately. (b) PDFs for *S* from separate Process, Historical and Paleoclimate (LGM combined with mPWP or PETM) evidence. (c) Combined evidence PDFs derived using, as Paleoclimate evidence, that from the LGM combined with that from either the mPWP (black line, with the green line showing Sherwood20's actual primary PDF) or the PETM (magenta line). The bars show 17–83% ranges, with disks marking medians (50th percentiles). (d) Unnormalized PDFs for *S* and S_{hist}. These account for probability outside 0–20 K, which is substantial when using S20's original assumptions. Note: 1 K = 1°C

The effects on *S* estimation of the various corrections of and revisions to both statistical estimation methods and data-variable estimates are tabulated in Appendix D, along with information about the revisions made to data-variable estimates. In summary, the corrections and revisions that I made in relation to data-variables fall into four categories, the substance and effects of each being:

(i) adjusting the $F_{2\times CO2}$ value used for inferring *S* from Process and Historical evidence to reflect the effect of climate feedback changing over GCM abrupt4xCO2 simulations, as should undoubtedly be done. This corrects an important conceptual error in Sherwood regarding the appropriate measure of $F_{2\times CO2}$ to use (see Appendix C). Also aligning the CO_2 concentration changes used when estimating the ECS to *S* ratio, thereby eliminating an inconsistency between Sherwood20's treatment of Paleoclimate evidence and non-Paleoclimate evidence, and adopting the AR6 assessment of $F_{2\times CO2}$ and of the slightly non-logarithmic relationship of CO_2 ERF with concentration. These changes reduce the median *S* estimate by 0.4°C;

(ii) adopting AR6 assessments of Historical non-aerosol ERFs and the GMAT−GMST warming relationship. Doing so reduces the median *S* estimate by a further 0.2°C;

(iii) going on to change some of S20's other data-variable estimates to reflect purely more recent evidence than that used in Sherwood20. Doing so causes in total a 0.4°C reduction in the median *S* estimate, with revising the difficult to evaluate cloud feedback estimate accounting for 0.15°C of this;

(iv) using arguably better justified (albeit not based purely on more recent information), alternative estimates for a few other data-variables. Reevaluating existing evidence regarding warming and ERF changes since the LGM causes a further 0.1°C reduction in the median *S* estimate. Interestingly, going on to revise estimated historical aerosol ERF (substantially weakening Sherwood20's estimate of it) causes negligible further change in the *S* estimate.

Discussion and Conclusions

Sherwood20's approach of combining, using formal statistical methods, estimates of climate sensitivity derived from multiple lines of evidence that are independent of each other, while avoiding any direct dependence on GCM climate sensitivities, has much to recommend it. Unfortunately, the authors ignored published evidence that the statistical method they chose, which involved an investigator-selected prior distribution, could produce biased estimation when used for their purpose. Worse, they used a method to estimate the data likelihood functions that underlie their assessment that, from its description, appeared of questionable validity. Relatively simple checks confirmed that their likelihood estimation method was indeed unsound, in some cases hugely underestimating likelihood at high climate sensitivity values.

In practice, given Sherwood20's choice of prior distribution and their estimates of data-variable distributions, the evidence concerning climate sensitivity was sufficiently strong, when combining all lines of evidence, for the two foregoing statistical method problems to cause only minor bias (actually a slight underestimation) in their assessment of climate sensitivity.

However, conceptual errors, inconsistencies and inaccuracies in Sherwood20's treatment of CO_2 ERF (including $F_{2\times CO2}$) caused a significant overestimation of *S*. Fixing these and revising various other data-variable estimates, primarily reflecting more recent evidence than used in Sherwood20, results in a 30%+ reduction in their *S* estimate at all percentiles.

Sherwood20 do not estimate the Transient Climate Response (TCR), a measure of the multidecadal disequilibrium response to a doubling of CO_2 concentration, from their Historical evidence. However, TCR can be estimated by using their formula for estimating S_{hist} with the term that compensates for disequilibrium removed, and sampling from the Historical data-variable distributions (Otto et al. 2013; Lewis and Curry 2015, 2018). When doing so using Sherwood20's data-variable assumptions, and with no restriction on possible TCR values, the median TCR estimate is 2.26°C (17–83% range 1.7–4.45°C). This is well above the AR6 estimate (central value 1.8°C, *likely* range 1.4–2.2°C). Upon revising the data-variable distributions, the median TCR estimate falls to 1.54°C (17-83% range 1.25–2.0°C).

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Appendix A – Likelihood function-based parameter estimation

Various different statistical approaches may be used to estimate a variable like climate sensitivity whose value, while uncertain, is regarded as being fixed (a 'parameter'). However, underlying all these approaches is the data-based 'likelihood', a function of the unknown parameter value. The likelihood represents, for each possible parameter value, how likely (probable) to arise are the combinations of possible data-variable values that are consistent with that parameter value, given the uncertainty distributions of the data-variables and their mathematical relationship(s) with the parameter.

The two main statistical paradigms, Frequentist and Bayesian, differ in how to turn the likelihood into an estimate of the parameter of interest, with associated uncertainty ranges.

Frequentists use various methods to estimate 'confidence intervals' for the parameter from the likelihood function. Confidence intervals, if well-constructed and accurate, properly represent the uncertainty in the parameter value arising from random errors in the data-variable estimates. However, other than in simple cases, in practice obtaining accurate Frequentist estimates of confidence intervals from likelihoods is often difficult.

Bayesians instead weight the likelihood, at each parameter value, by a 'prior distribution' (prior) to obtain an estimated 'posterior' probability density function (PDF) for the parameter, which directly provides a central estimate and associated 'credible intervals' for it. In the dominant, Subjective Bayesian approach used in Sherwood20, the prior is a PDF representing the investigator's beliefs about the parameter value before incorporating information from the data-variable estimates. This widely-used approach is poorly suited to scientific inference, since in many cases the credible intervals it generates may be far from being confidence intervals, and thus may not properly represent uncertainty arising from errors in data-variable estimates.

In the alternative Objective Bayesian approach, the prior is a mathematically-calculated weighting function that primarily reflects how informative the data-variable estimates are about the parameter value. Such a 'noninformative' prior is intended to convey no preexisting knowledge regarding the parameter value, and is typically designed to produce credible intervals that match confidence intervals as closely as is practicable. This approach, used in Lewis22, is more suitable for scientific inference than a Subjective Bayesian approach.

Where multiple lines of evidence are involved, Subjective Bayesians normally incorporate the likelihood from each in turn, using the first posterior PDF obtained as the prior for the second likelihood, and so on ('Bayesian updating'). This method is not suitable when using an Objective Bayesian approach: the evidence must all be combined, and a prior derived that is noninformative for the combined evidence.

Appendix B – Sherwood20's unsound likelihood estimation

Satisfactory estimation of a parameter from data-variables requires a good estimate of its likelihood. Deriving such an estimate may not be straightforward where, as here, there is not a one-to-one correspondence between the data-variable and parameter values. However, there are some well-established simple methods that usually provide reasonably accurate likelihood estimates in such cases. I used the two most obvious such methods (the profile likelihood and data doubling methods; the latter could not be applied to estimate the likelihood from the historical record when using Sherwood20's peculiar input distribution for aerosol forcing). However, my primary likelihood estimates were derived using a sampling based 'integrated likelihood' method that I considered to be theoretically correct. In all cases the likelihood estimates from all the methods that I used were almost identical, providing confidence in their accuracy.

Sherwood20 used a single sampling-based likelihood estimation method of their own devising, which treats temperature change (ΔT) differently from all other input data-variables. Their method appeared to me to be invalid and likely, except in some simple cases, to produce erroneous results, at least where a data-variable involved has substantial asymmetrical uncertainty or *S* is related to it non-linearly. These circumstances occur for Sherwood20's historical likelihoods (for both *S* and S_{hist}) and warm paleoclimate period likelihoods, particularly that for the PETM. In such cases, using Sherwood20's method the calculated likelihood is highly sensitive to changing the input data-variable that is given different treatment from the others. If the method were valid, changing the data-variable that is given different treatment should have no effect on the likelihood estimate, since all data-variables have identical status in the relevant equations.

Figure 2 shows that Sherwood20's Historical likelihoods, particularly that for S_{hist}, differ greatly at high sensitivity values from those that I estimate using my sampling-based method, which are significantly higher. Estimates given by the alternative, well established, method used in Lewis22 that can be applied to Sherwood20's Historical data-variable input distributions are almost identical to those from my sampling-based method.

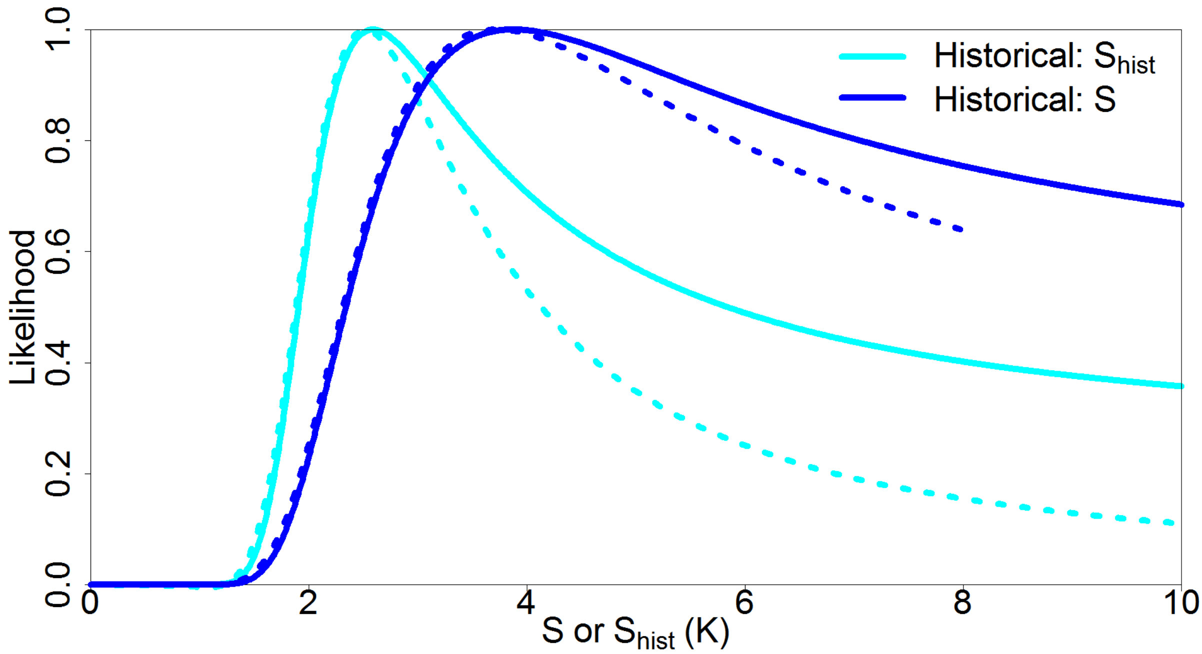

Fig.2 Historical likelihoods for *S* and S_{hist} using Sherwood20's input assumptions (data-variable probability distributions). Dotted lines are digitized from Sherwood20, solid lines are per Lewis22's primary 'integrated likelihood' estimation method. Note: The Sherwood20 figure from which Historical *S* was digitized only extended to *S* = 8 K. Note: 1 K = 1°C

Figure 3 compares Sherwood20 and Lewis22 PETM paleoclimate likelihood estimates for *S*. Doing so is complicated by a factor-of-ten error in the standard deviation for the CO_2 change (ΔCO2) in Sherwood20's PETM code. The magenta lines shows what their likelihood estimate would have been had they used their stated ΔCO2 standard deviation. It deviates substantially across the range of *S* values from that calculated using Lewis22's primary integrated likelihood method (dotted dark blue line), which agrees almost exactly to estimates given by both alternative, well established, likelihood estimation methods used in Lewis22 (not shown). The green line shows that results using Sherwood20's likelihood estimation method.

The fact that likelihood estimates from all the methods employed in Lewis22 agree, but differ substantially from those per Sherwood20 for Historical and PETM evidence, cases where I would expect their method to fail, shows that their likelihood estimation method is unsound. The sensitivity to which input data-variable is given different treatment from the others (green and magenta lines in Figure 3) provides further evidence of the invalidity of Sherwood20's method. Further evidence for Sherwood20's Historical likelihood estimates being unrealistic is given in Lewis22.

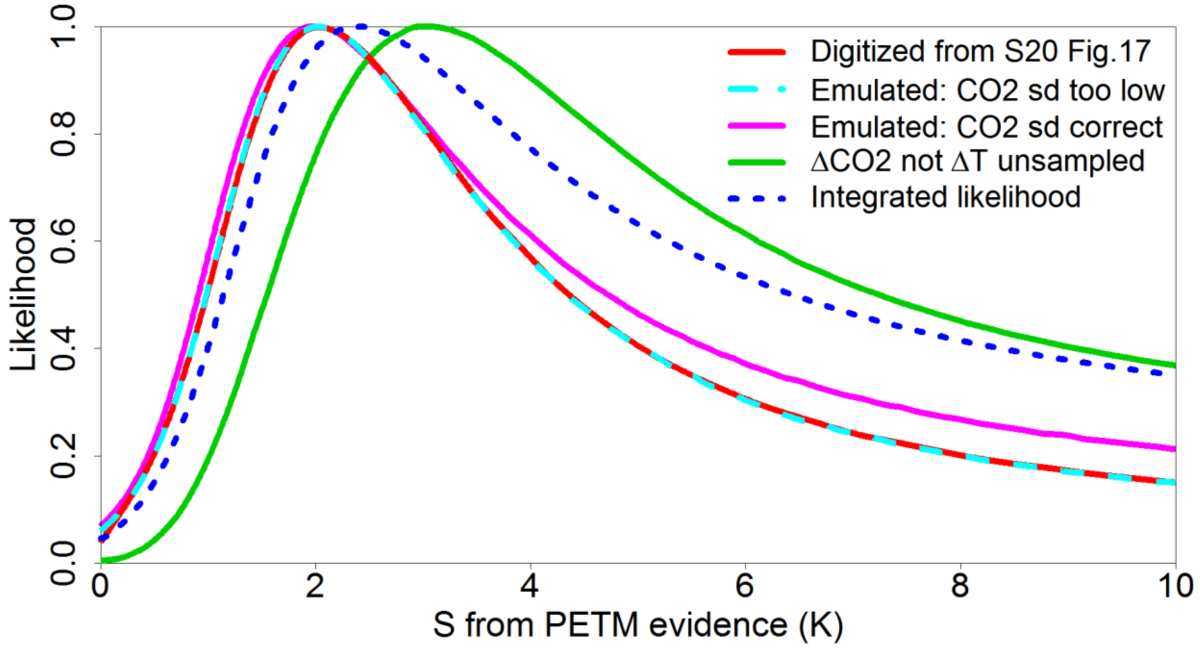

Fig.3 PETM paleoclimate likelihoods for *S* using Sherwood20's input assumptions. The solid red line is digitized from Sherwood20; due to a coding error this used a standard deviation for CO_2 that was too small by a factor of ten. The dash cyan line overlying it and the solid magenta lines are per code emulating Sherwood20's likelihood estimate method, using respectively the incorrect and the correct CO_2 standard deviation; the solid green line shows that changing the data-variable singled out for different treatment from ΔT to ΔCO2 would greatly change Sherwood20's estimated likelihood. The dotted blue line is per Lewis22's primary 'integrated likelihood' estimation method.

Appendix C – The correct $F_{2\times CO2}$ estimate to use with Process and Historical evidence

As explained, the proxy S for ECS that Sherwood20 target corresponds to estimating ECS by linearly projecting, using a regression relationship, warming (ΔT) occurring over the 150 years following a hypothetical abrupt quadrupling of preindustrial CO_2 concentration ('abrupt4×CO2') to the point of zero top-of-atmosphere radiative imbalance ($\Delta N = 0$). That corresponds to the x-axis intercept of the black line in Figure 4, which shows annual ΔT and ΔN values from the MRI-ESM2-0 model's abrupt4×CO2 simulation, scaled by 0.49 so that the model's estimated actual $F_{2\times CO2}$ equals the AR6 best estimate of $F_{2\times CO2}$ (3.93 Wm^{-2}, shown by the magenta cross). Accordingly, $S = F_{2\times CO2}^{regress} / (-\lambda)$, where $F_{2\times CO2}^{regress}$ and the climate feedback estimate λ are respectively the black line's y-axis intercept and its slope. The underestimation by $F_{2\times CO2}^{regress}$ of the model's actual $F_{2\times CO2}$ is a consequence of its climate feedback (the local slope of ΔN against ΔT) weakening over time, as typically occurs in GCMs.

Sherwood20 recognize that $-\lambda$ should be divided into $F_{2\times CO2}^{regress}$ when estimating S in GCM abrupt4×CO2 simulations, conceding a similar overestimation of S to the 16% I estimate if instead dividing it into the actual value of $F_{2\times CO2}$. It is self-evident that the same is true when climate feedback is estimated on a basis consistent with the estimation of λ from abrupt4×CO2 GCM simulations. That is the case for Process evidence. It is also the case for Historical evidence, where Sherwood20 explicitly adjust the initial energy-balance based climate feedback estimate ($[\Delta N - \Delta ERF]/\Delta T$, changes being measured between averages over 1861– 80 and 2006–18, represented by the slope of the blue line in Figure 4), so as to be on the same basis as estimates of λ for GCMs when regressing over 150-year abrupt4xCO2 simulations.

However, Sherwood20 incorrectly used their $F_{2\times CO2}$ value rather than $F_{2\times CO2}^{regress}$ when estimating S from both Process and Historical evidence, wrongly asserting that the related overestimation issue only affects S estimation for GCMs. This misconception results in Sherwood20's estimates of S from Process and Historical evidence being biased high.

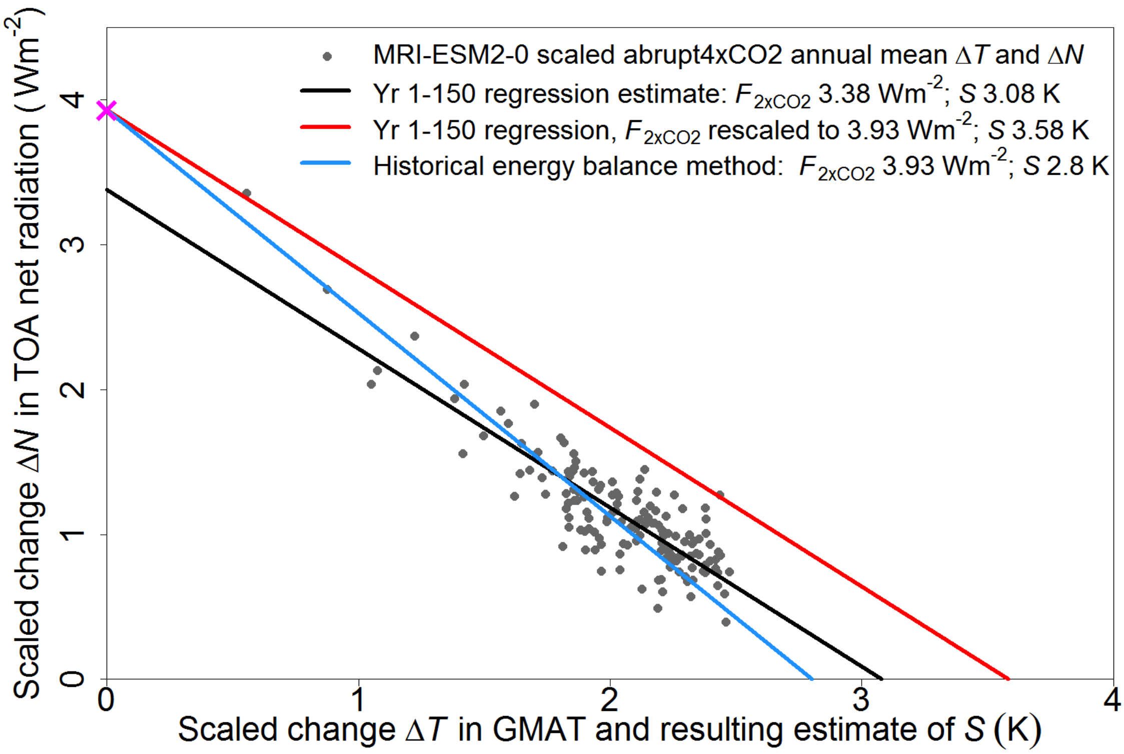

Fig.4. Illustration of the need to scale the actual $F_{2\times CO2}$ to avoid overestimation of S. The plot shows annual mean abrupt4×CO2 values during the 150-year abrupt4×CO2 simulation by the MRI-ESM2-0 GCM (scaled by 0.49); the year one value is the leftmost grey dot. The black line shows the linear regression fit for those points (with slope λ and y-axis intercept $F_{2\times CO2}^{regress}$, a biased estimate of $F_{2\times CO2}$) and the resulting correct S estimate (the x-axis intercept). The red line shows the overestimation of S resulting from use of $F_{2\times CO2}$ instead of $F_{2\times CO2}^{regress}$, using the same slope as the black line (being λ). The blue line corresponds to estimation of climate sensitivity for the GCM using the same energy-balance basis as for unadjusted estimation of climate feedback and climate sensitivity from Historical evidence, using average ΔN and ΔT values over the first 100 simulation years, with ΔERF being $F_{2\times CO2}$ (3.93 Wm^{-2}, shown by the magenta cross) and the resulting slope correctly divided into $-F_{2\times CO2}$. The adjustment made by Sherwood 20 to the energy-balance estimate of climate feedback is intended to alter the slope of the blue line to equal that of the black line, which results in overestimation of S if combined with use of $F_{2\times CO2}$ (giving the red line) rather than $F_{2\times CO2}^{regress}$ (giving the black line).

Appendix D – Reconciling Sherwood20's and Lewis22's climate sensitivity estimates

Percentile of posterior PDF for S (as %)	5%	17%	50%	83%	95%
	°C	°C	°C	°C	°C
Per Sherwood20's Baseline (main) results	2.3	2.6	**3.1**	3.9	4.7
Using valid likelihood estimates instead of Sherwood20's	2.25	2.6	3.16	4.0	4.85
Also using Objective Bayesian computed prior, not Sherwood20's	2.3	2.65	**3.23**	4.1	5.05
After cumulative changes related to CO_2 ERF & other data-variables					
Using CO_2 ERFs consistent with abrupt2/4x simulations & AR6	1.95	2.3	**2.82**	3.6	4.35
Adopting AR6 Historical non-aerosol ERFs & ΔT basis[a]	1.85	2.15	**2.64**	3.35	4.1
Using later data/newer evidence when estimating certain other non-cloud feedback data-variables [bcd]	1.7	1.95	**2.39**	3.0	3.65
Revising cloud feedback, per newer evidence[e]	1.6	1.85	**2.25**	2.8	3.4
Revising LGM ΔT and ΔF_{exCO2} (revaluation of existing evidence)[fg]	1.55	1.75	**2.15**	2.7	3.25
Revising also Historical aerosol ERF, per newer and other evidence[h]	1.55	1.75	**2.16**	2.7	3.2

Notes

[a] AR6 Historical ERF time series are used to estimate ΔF_{other}, but only to scale the main 1850 to 2005−2015 $\Delta F_{aerosol}$ estimate to a 1861−80 to 2006−18 change. Adopting AR6 estimates of Historical non-aerosol ERFs (and of non-unit efficacy in one case) increases the median change in non-CO_2 non-aerosol efficacy-adjusted ERF from 1.20 to 1.53 Wm^{-2}, while reducing the CO_2 ERF change from 1.73 to 1.72 Wm^{-2}. Adopting the AR6 ΔT basis changes S20's Historical GMAT – GMST adjustment to match the AR6 zero-median estimate of their difference.

[b] Planck feedback (median −3.25 not −3.20 $Wm^{-2}K^{-1}$): Zelinka et al. (2020); supplement S5.1.2.

[c] Historical pattern effect (median 0.35 not 0.50 Wm^{-2}): Lewis and Mauritsen (2021); Zhou et al. (2021); Fueglistaler and Silvers (2021); supplement S5.2.4.

[d] mPWP ΔT (median 2.48 not 3.00°C) and Earth System Sensitivity/ECS ratio (median 1.67 not 1.5): Haywood et al. (2020); supplement S5.3.3.

[e] Tropical & mid-latitude marine low cloud feedback (median 0.19 not 0.37 $Wm^{-2}K^{-1}$): Myers et al. (2021), Cessana and Del Genio (2021), Mülmenstädt et al. (2021); supplement S5.1.3.

[f] LGM ΔT (median −4.5 not −5.0°C): revised towards mean cooling per those studies cited by Sherwood20 of 4.2°C (adjusted to change from preindustrial not mid/late Holocene where relevant); supplement S5.3.2

[g] LGM ΔF_{exCO2} (median change in non-CO_2 ERF revised from −6.15 Wm^{-2} to −6.67 Wm^{-2}), due to inclusion of omitted albedo change due to fall in sea level exposing more land surface: Kohler et al. (2010); Zhu and Poulsen 2021; supplement S5.3.2.

[h] Multiple studies, e.g. Hamilton et al. (2018); Gryspeerdt et al. (2019); Paulot et al. (2020); Possner et al. (2020); Glassmeier et al. (2021); Lee et al. (2021); Liu et al. (2021); supplement S5.2.3. Over the same 1850 to 2005–15 period, the revised Historical aerosol ERF distribution is weaker (median −0.95 Wm^{-2} rather than −1.18 Wm^{-2}), and is Gaussian (like the AR6 estimate, and with the same standard deviation) rather than strongly negatively skewed.

References

Lewis (2022) Objectively combining climate sensitivity evidence. Climate Dynamics, doi.org/10.1007/s00382-022-06468-x

See Lewis (2022) and its Supporting Information for further information and full references.