

# An assessment of Earth's climate sensitivity using multiple lines of evidence

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## Key Points:

- We assess evidence relevant to Earth's climate sensitivity  $S$ : feedback process understanding, and the historical and paleo-climate records.
- All three lines of evidence are difficult to reconcile with  $S < 2$  K, while paleo evidence provides the strongest case against  $S > 4.5$  K.
- A Bayesian calculation finds a 66% range of 2.6-3.9 K, which remains within the bounds 2.3-4.5 K under plausible robustness tests.

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# 146 Abstract

147

148 We assess evidence relevant to Earth's equilibrium climate sensitivity per doubling of  
149 atmospheric CO<sub>2</sub>, characterized by an effective sensitivity  $S$ . This evidence includes  
150 feedback process understanding, the historical climate record, and the paleoclimate  
151 record. An  $S$  value lower than 2 K is difficult to reconcile with any of the three lines of  
152 evidence. The amount of cooling during the Last Glacial Maximum provides strong  
153 evidence against values of  $S$  greater than 4.5 K. Other lines of evidence in combination  
154 also show that this is relatively unlikely. We use a Bayesian approach to produce a  
155 probability density (PDF) for  $S$  given all the evidence, including tests of robustness to  
156 difficult-to-quantify uncertainties and different priors. The 66% range is 2.6-3.9 K for our  
157 Baseline calculation, and remains within 2.3-4.5 K under the robustness tests;  
158 corresponding 5-95% ranges are 2.3-4.7 K, bounded by 2.0-5.7 K (although such high  
159 confidence ranges should be regarded more cautiously). This indicates a stronger  
160 constraint on  $S$  than reported in past assessments, by lifting the low end of the range. This  
161 narrowing occurs because the three lines of evidence agree and are judged to be largely  
162 independent, and because of greater confidence in understanding feedback processes  
163 and in combining evidence. We identify promising avenues for further narrowing the range  
164 in  $S$ , in particular using comprehensive models and process understanding to address  
165 limitations in the traditional forcing-feedback paradigm for interpreting past changes.  
166

## 167 Plain Language Summary

168

169 Earth's global "climate sensitivity" is a fundamental quantitative measure of the susceptibility of  
170 Earth's climate to human influence. A landmark report in 1979 concluded that it probably lies  
171 between 1.5-4.5°C per doubling of atmospheric carbon dioxide, assuming that other influences on  
172 climate remain unchanged. In the 40 years since, it has appeared difficult to reduce this  
173 uncertainty range. In this report we thoroughly assess all lines of evidence including some new  
174 developments. We find that a large volume of consistent evidence now points to a more confident  
175 view of a climate sensitivity near the middle or upper part of this range. In particular, it now  
176 appears extremely unlikely that the climate sensitivity could be low enough to avoid substantial  
177 climate change (well in excess of 2°C warming) under a high-emissions future scenario. We remain  
178 unable to rule out that the sensitivity could be above 4.5°C per doubling of carbon dioxide levels,  
179 although this is not likely. Continued research is needed to further reduce the uncertainty and we  
180 identify some of the more promising possibilities in this regard.

# 181 1 Introduction

182

183 Earth's equilibrium climate sensitivity (ECS), defined generally as the steady-state global  
184 temperature increase for a doubling of CO<sub>2</sub>, has long been taken as the starting point for  
185 understanding global climate changes. It was quantified specifically by Charney et al. (National  
186 Research Council, 1979) as the equilibrium warming as seen in a model with ice sheets and  
187 vegetation fixed at present-day values. Those authors proposed a range of 1.5-4.5 K based on the  
188 information at the time, but did not attempt to quantify the probability that the sensitivity was inside  
189 or outside this range. The most recent report by the Intergovernmental Panel on Climate Change  
190 (Stocker et al., 2013) asserted the same now-familiar range, but more precisely dubbed it a >66%

191 (“likely”) credible interval, implying an up to one in three chance of being outside that range. It has  
192 been estimated that—in an ideal world where the information would lead to optimal policy  
193 responses—halving the uncertainty in a measure of climate sensitivity would lead to an average  
194 savings of US\$10 trillion in today’s dollars (Hope, 2015). Apart from this, the sensitivity of the  
195 world’s climate to external influence is a key piece of knowledge that humanity should have at its  
196 fingertips. So how can we narrow this range?

197  
198 Quantifying ECS is challenging because the available evidence consists of diverse strands, none  
199 of which is conclusive by itself. This requires that the strands be combined in some way. Yet,  
200 because the underlying science spans many disciplines within the Earth Sciences, individual  
201 scientists generally only fully understand one or a few of the strands. Moreover, the interpretation  
202 of each strand requires structural assumptions that cannot be proven, and sometimes ECS  
203 measures have been estimated from each strand that are not fully equivalent. This complexity and  
204 uncertainty thwarts rigorous, definitive calculations and gives expert judgment and assumptions a  
205 potentially large role.

206  
207 Our assessment was undertaken under the auspices of the World Climate Research Programme's  
208 Grand Science Challenge on Clouds, Circulation and Climate Sensitivity following a 2015  
209 workshop at Ringberg Castle in Germany. It tackles the above issues, addressing three  
210 questions:

- 211  
212 1) Given all the information we now have, acknowledging and respecting the uncertainties,  
213 how likely are very high or very low climate sensitivities, i.e., outside the presently accepted  
214 likely range of 1.5-4.5 K (IPCC, 2013)?
- 215 2) What is the strongest evidence against very high or very low values?
- 216 3) Where is there potential to reduce the uncertainty?

217 In addressing these questions, we broadly follow the example of Stevens et al. (2016, hereafter  
218 SSBW16) who laid out a strategy for combining lines of evidence and transparently considering  
219 uncertainties. The lines of evidence we consider, as in SSBW16, are modern observations and  
220 models of system variability and feedback processes; the rate and trajectory of historical warming;  
221 and the paleoclimate record. The core of the combination strategy is to lay out all the  
222 circumstances that would have to hold for the climate sensitivity to be very low or high given all the  
223 evidence (which SSBW16 call “storylines”). A formal assessment enables quantitative probability  
224 statements given all evidence and a prior distribution, but the “storyline” approach allows readers  
225 to draw their own conclusions about how likely the storylines are, and points naturally to areas with  
226 greatest potential for further progress. Recognizing that expert judgment is unavoidable, we  
227 attempt to incorporate it in a transparent and consistent way (e.g., Oppenheimer et al., 2016).

228  
229 Combining multiple lines of evidence will increase our confidence and tighten the range of likely  
230 ECS if the lines of evidence are broadly consistent. If uncertainty is underestimated in any  
231 individual line of evidence—inappropriately ruling out or discounting part of the ECS range—this  
232 will make an important difference to the final outcome (see example in Knutti et al., 2017).  
233 Therefore, it is vital to seek a comprehensive estimate of the uncertainty of each line of evidence  
234 that accounts for the risk of unexpected errors or influences on the evidence. This must ultimately  
235 be done subjectively. We will therefore explore the uncertainty via sensitivity tests and by  
236 considering ‘what if’ cases in the sense of SSBW16, including what happens if an entire line of  
237 evidence is dismissed.

238

239 The most recent reviews (Collins et al., 2013, Knutti et al., 2017) have considered the same three  
240 main lines of evidence considered here, and have noted they are broadly consistent with one  
241 another, but did not attempt a formal quantification of the PDF of ECS. Formal Bayesian  
242 quantifications have been done based on the historical warming record (see Bodman and Jones  
243 2016 for a recent review), the paleoclimate record (PALAEOSENS, 2012), a combination of  
244 historical and last millennium records (Hegerl et al., 2006), and multiple lines of evidence from  
245 instrumental and paleo records (Annan and Hargreaves, 2006). An assessment based only on a  
246 subset of the evidence will yield too wide a range if the excluded evidence is consistent (e.g.  
247 Annan and Hargreaves, 2006), but if both subsets rely on similar information or assumptions, this  
248 co-dependence must be considered when combining them (Knutti and Hegerl 2008). Therefore, an  
249 important aspect of our assessment is to explicitly assess how uncertainties could affect more than  
250 one line of evidence (cf. section 6), and to assess the sensitivity of calculated PDFs to reasonable  
251 allowance for interdependencies of the evidence.

252

253 Another key aspect of our assessment is that we explicitly consider process understanding via  
254 modern observations and process models as a newly robust line of evidence (section 3). Such  
255 knowledge has occasionally been incorporated implicitly (via the prior on ECS) based on the  
256 sample distribution of ECS in available climate models (Annan and Hargreaves, 2006) or expert  
257 judgments (Forest et al., 2002), but climate models and expert judgments do not fully represent  
258 existing knowledge or uncertainty relevant to climate feedbacks, nor are they fully independent of  
259 other evidence (in particular that from the historical temperature record, see Kiehl, 2007). Process  
260 understanding has recently blossomed, however, to the point where substantial statements can be  
261 made without simply relying on climate model representations of feedback processes, creating a  
262 new opportunity exploited here.

263

264 Climate models (specifically general circulation models, or GCMs) nonetheless play an increasing  
265 role in calculating what our observational data would look like under various hypothetical ECS  
266 values—in effect translating from evidence to ECS. Their use in this role is now challenging long-  
267 held assumptions, for example showing that 20th-century warming could have been relatively  
268 weak even if ECS were high (section 4), that paleoclimate changes are strongly affected by factors  
269 other than CO<sub>2</sub>, and that climate may become more sensitive to greenhouse gases in warmer  
270 states (section 5). GCMs are also crucial for confirming how modern observations of feedback  
271 processes are related to ECS (section 3). Accordingly, another novel feature of this assessment  
272 will be to use GCMs to refine our expectations of what observations should accompany any given  
273 value of ECS and thereby avoid biases now evident in some estimates of ECS based on the  
274 historical record using simple energy budget or energy balance model arguments. GCMs are also  
275 used to link global feedback strengths to observable phenomena. However, for reasons noted  
276 above, we avoid relying on GCMs to tell us what values to expect for key feedbacks except where  
277 the feedback mechanisms can be calibrated against other evidence. Since we use GCMs in some  
278 way to help interpret all lines of evidence, we must be mindful that any errors in doing this could  
279 reinforce across lines (see section 6.2).

280

281 We emphasize that this assessment begins with the evidence on which previous studies were  
282 based, including new evidence not used previously, and aims to comprehensively synthesize the  
283 implications for climate sensitivity both by drawing on key literature and by doing new calculations.  
284 In doing this, we will identify structural uncertainties that have caused previous studies to report  
285 different ranges of ECS from (essentially) the same evidence, and account for this when assessing  
286 what that underlying evidence can tell us.

287  
288 An issue with past studies is that different or vague definitions of ECS may have led to perceived,  
289 unphysical discrepancies in estimates of ECS that hampered abilities to constrain its range and  
290 progress understanding. Bringing all the evidence to bear in a consistent way requires using a  
291 specific measure of ECS, so that all lines of evidence are linked to the same underlying quantity.  
292 We denote this quantity  $S$  (see section 2.1). The implications for  $S$  of the three strands of evidence  
293 are examined separately in sections 3-5, and anticipated dependencies between them are  
294 discussed in section 6. To obtain a quantitative PDF of  $S$ , we follow SSBW16 and many other  
295 studies by adopting a Bayesian formalism, which is outlined in sections 2.2-2.6. The results of  
296 applying this to the evidence are presented in section 7, along with the implications of our results  
297 for other measures of climate sensitivity and for future warming. The overall conclusions of our  
298 assessment are presented in section 8. We note that no single metric such as  $S$  can fully describe  
299 or predict climate responses, and we discuss its limitations in section 8.2, as well as implications of  
300 our work for future research.

301  
302 While we endeavor to write for a broad audience, it is necessary to dip into technical detail in order  
303 to support the reasoning and conclusions, and some of the methods used are novel and require  
304 explanation. We have therefore structured this assessment so that the discussions of the three  
305 lines of evidence (sections 3-5) are quasi-independent, with separate introductions, detailed  
306 analyses, and conclusions. Readers who are not interested in the details can gain an overview of  
307 the key points from the concluding portions of these sections. Likewise, readers not interested in  
308 details of the statistical method could skip most of section 2 and focus on the “storylines”  
309 presented in sections 3-5. The probabilities given in section 7 derive from the statistical method,  
310 but the independence issues discussed in section 6 are important for either quantitative or  
311 qualitative assessment of the evidence.

312  
313

## 314 **2. Methods**

315  
316 This section first explains the measure of ECS we will use and how it relates to others (section  
317 2.1), then presents the simple physical model used to interpret evidence (section 2.2). Section 2.3  
318 summarizes the overall methodology, and section 2.4 goes over this in more detail, beginning with  
319 a basic review of Bayesian inference intended mainly for those new to the topic while focusing on  
320 concepts relevant to the ECS problem (section 2.4.1), then working through the solution of the  
321 model and sampling approach (sections 2.4.2-2.4.4). For other basic introductions to Bayesian  
322 inference, see Stone (2012) or Gelman et al. (2013).

323

### 324 **2.1 Measures of climate sensitivity**

325  
326 Climate sensitivity is typically quantified as warming per doubling of  $\text{CO}_2$ , but this is by tradition.  
327 One could also consider the warming per unit radiative forcing, or the increment of additional net  
328 power exported to space per unit warming (the feedback parameter, i.e, energetic “spring  
329 constant” of the system) denoted  $\lambda$ . Indeed (see sections 2.2 and later) we will find it easier to write  
330 our evidence in terms of  $\lambda$  rather than warming-per-doubling (ECS), making the definition of an  
331 ECS optional. One can imagine a range of  $\text{CO}_2$  forcing scenarios, each yielding its own value for

332 the ECS; each such scenario also implies a matching value for  $\lambda$ . Our approach simultaneously  
333 constrains both  $\lambda$  and  $S$  (see section 2.3).  
334

335 In choosing the reference scenario to define sensitivity for this assessment, for practical reasons  
336 we depart from the traditional Charney ECS definition (equilibrium response with ice sheets and  
337 vegetation assumed fixed) in favor of a comparable and widely used, so-called “effective climate  
338 sensitivity”  $S$  derived from system behavior during the first 150 years following a (hypothetical)  
339 sudden quadrupling of  $\text{CO}_2$ . During this time the system is not in equilibrium, but regression of  
340 global-mean top-of-atmosphere energy imbalance onto global-mean near-surface air temperature,  
341 extrapolated to zero imbalance, yields an estimate of the long-term warming valid if the average  
342 feedbacks active during the first 150 years persisted to equilibrium (Gregory et al., 2004). This  
343 quantity therefore approximates the long-term Charney ECS (e.g., Danabasoglu and Gent, 2009),  
344 though how well it does so is a matter of active investigation addressed below. Our reference  
345 scenario does not formally exclude any feedback process, but the 150-year time frame minimizes  
346 slow feedbacks (especially ice sheet changes).  
347

348 This choice involves weighing competing issues. Crucially, effective sensitivity (or other measures  
349 based on behavior within a century or two of applying the forcing) is more relevant to the time  
350 scales of greatest interest (i.e., the next century) than is equilibrium sensitivity, and effective  
351 sensitivity has been found to be strongly correlated ( $r=0.95$ ) with the magnitude of model-simulated  
352 21st-century warming under a high-emission scenario (Gregory et al., 2015, Grose et al., 2017,  
353 2018). It is also widely available from climate models (e.g., Andrews et al., 2012) which facilitates  
354 many steps in our analysis. All candidate climate sensitivity measures are based on an outcome of  
355 a hypothetical scenario never realized on Earth. Ultimately models or theory are required to relate  
356 the outcome of any one scenario to that of any other. The ideal measure  $S$  is one that is as closely  
357 related as possible to scenarios of practical interest: those which produced evidence (e.g., the  
358 historical  $\text{CO}_2$  rise), or which might occur in the future. Effective sensitivity is a compromise that is  
359 relatively well related to both the available past evidence and projected future warmings .  
360

361 The Transient Climate Response (TCR, or warming at the time of  $\text{CO}_2$  doubling in an idealized 1%  
362 per year increase scenario), has been proposed as a better measure of warming over the near- to  
363 medium-term; it may be more generally related to peak warming, and better constrained (in  
364 absolute terms) by historical warming, than  $S$  (Frame et al., 2005; Froelicher et al., 2013). It may  
365 also be better at predicting high-latitude warming (Grose et al., 2017). But as mentioned above,  
366 21st-century global-mean trends under high emissions are better predicted by  $S$  than by TCR,  
367 perhaps because of nonlinearities in forcing or response (Gregory et al., 2015) or because TCR  
368 estimates are affected by noise (Sanderson, 2020). TCR is also less directly related to the other  
369 lines of evidence than is  $S$ . In this study we will briefly address TCR in sections 4 and 7.4, but will  
370 not undertake a detailed assessment.  
371

372 The IPCC (at least through AR5) formally retains a definition of ECS based on long-term  
373 equilibrium. Much of the information they use to quantify ECS however exploits GCM calculations  
374 of effective (e.g., Andrews et al., 2012), not equilibrium, sensitivity, and it appears that the  
375 distinction is often overlooked. In this report, we will use “long-term” to describe processes and  
376 responses involved in the effective sensitivity  $S$ , and “equilibrium” for the fully equilibrated ECS.  
377 The ECS differs from  $S$  due to responses involving the deep ocean, atmospheric composition and  
378 land surface that emerge on centennial time scales (e.g., Frey and Kay, 2018; see section 5),  
379 though calculations here (following Charney and past IPCC reports) do not include ice-sheet  
380 changes.



381  
382 To calculate the ECS in a fully coupled climate model requires very long integrations (>1000  
383 years). Fortunately, a recent intercomparison project (LongrunMIP; Rugenstein et al., 2019a) has  
384 organized long simulations from enough models to now give a reasonable idea of how ECS and S  
385 are likely to be related.

386  
387 Relationships between S and several other quantities are shown in Fig. 1 from available  
388 models. Predicted S is reasonably well correlated with the other sensitivity measures (Fig. 1 a),  
389 indicating that S is a useful measure, but also that the conclusions of this assessment would still  
390 hold if another measure were used. Note that we do not consider here all possible measures; see  
391 Rugenstein et al. (2019b) for a discussion of some additional ones, which also generally correlate  
392 well with S. S is less well correlated to TCR ( $r=0.81$ ) than to ECS ( $r=0.94$ ), as expected since the  
393 TCR is sensitive to ocean heat uptake efficiency as well as to  $\lambda$ .

394  
395 Although the measures correlate well, all available LongRunMIP models equilibrate to a higher  
396 warming at  $4xCO_2$  than S from the same simulation (Fig. 1 a, small symbols; details of how the  
397 equilibrium is estimated are given in Rugenstein et al. (2019a,b). The median equilibrium warming  
398 per doubling at  $4xCO_2$  is 17% higher than the median S, suggesting a robust amplifying impact of  
399 processes too slow to emerge in the first 150 years. This occurs due to responses of the climate  
400 system on multidecadal to millennial time scales, including “pattern effects” from differences  
401 between ocean surface warming patterns that have not fully equilibrated within the first century or  
402 two (sections 3.3.2, 4.2); slow responses of vegetation; and temperature dependence of  
403 feedbacks. Evidence also shows, however (section 5.2.3), that sensitivity to two doublings (as  
404 assumed for S) is somewhat greater than that to one doubling. This state-dependence partly  
405 cancels out the low bias in the 150-year regression, leading to an ECS (for one doubling) that  
406 averages only 6% greater than S over the simulations, although the ratio of the two is uncertain so  
407 we assign an uncertainty of  $\pm 20\%$  (about 50% wider than the sample standard deviation in the  
408 available GCMs). Thus, statements about S in this assessment can also be interpreted, to  
409 relatively good approximation, as statements about ECS for one doubling of  $CO_2$ . (We use the  
410 symbol  $\zeta$  to represent this difference, with  $1+\zeta$  therefore being the ratio of our target S to the long-  
411 term equilibrium.)

412  
413 Fig. 1 b shows the relationships of S to future warming. The warming trend over the 21st  
414 century (Fig. 1 b) is also well correlated with S, especially for the highest-emission scenario  
415 RCP8.5. The correlations are not quite as strong for the weaker-forcing cases, suggesting that  
416 global temperature changes are harder to predict (in a relative sense) in more highly mitigated  
417 scenarios. This is mostly due to a weaker warming signal, but there is also a slightly greater model  
418 spread, reasons for which are not currently understood.

419  
420 To conclude, the effective sensitivity S that we will use—a linear approximation to the equilibrium  
421 warming based on the first 150 years after an abrupt  $CO_2$  quadrupling—is a practical option for  
422 measuring sensitivity, based on climate system behavior over the most relevant time frame while  
423 still approximating the traditional ECS. Moreover, the quantitative difference between this and the  
424 traditional equilibrium measure based on a  $CO_2$  doubling (with fixed ice sheets) appears to be  
425 small, albeit uncertain. This uncertainty is skewed, in the sense that long-term ECS could be  
426 substantially higher than S but is very unlikely to be substantially lower. Further work is needed to  
427 better understand and constrain this uncertainty.

428

## 429 2.2 Physical model

430

431 Here we review the equations that will be used to relate the evidence to the key unknowns.  
432 According to the conventional forcing-feedback theory of the climate system, the net downward  
433 radiation imbalance  $\Delta N$  at the top-of-atmosphere (TOA) can be decomposed into a radiative  
434 forcing  $\Delta F$ , a radiative response  $\Delta R$  due directly or indirectly to forced changes in temperature  
435 which is the feedback, and variability  $V$  unrelated to the forcing or feedback:

436

$$437 \quad \Delta N = \Delta F + \Delta R + V \quad (1)$$

438 Variability  $V$  can arise due to unforced variations in upwelling of cold water to the surface, cloud  
439 cover, albedo, etc. The net radiation balance  $\Delta N$  consists of the net absorbed shortwave (SW)  
440 solar radiation minus the planet's emission of longwave (LW) radiation. Taking the radiative  
441 response  $\Delta R$  as proportional to first order to the forced change in global mean surface air  
442 temperature  $\Delta T$ , equation (1) becomes

$$443 \quad \Delta N = \Delta F + \lambda \Delta T + V \quad (2)$$

444 where the climate feedback parameter  $\lambda$  is defined as the sensitivity of the net TOA downward  
445 radiation  $N$  to  $T$ ,  $dN/dT$ , (at fixed  $F$ ). If this feedback parameter is negative, the system is stable.

446 In equilibrium over sufficiently long time-scales (assuming  $\lambda < 0$ ) the net radiation imbalance  $\Delta N$  and  
447 mean unforced variability  $V$  will each be negligible, leaving a balance between the (constant)  
448 forcing  $\Delta F$  and radiative response  $\Delta R$ . In this case equation (2) can be written

$$449 \quad \Delta T = -\Delta F / \lambda \quad (3)$$

450 The case of a doubling of  $\text{CO}_2$  defines the climate sensitivity

$$451 \quad S = -\frac{\Delta F_{2\times\text{CO}_2}}{\lambda}, \quad (4)$$

452

453 where  $\Delta F_{2\times\text{CO}_2}$  is defined as the radiative forcing per  $\text{CO}_2$  doubling (noting that since our reference  
454 scenario involves two doublings,  $\Delta F_{2\times\text{CO}_2}$  is defined as half the effective forcing in that scenario).  
455 Estimation of this quantity is discussed in section 3.2.1. Note that while the above equations  
456 assume equilibrium, our reference scenario (section 2.1) is not an equilibrium scenario; however,  
457 because in this scenario  $\Delta N$  is zero (by construction) at the time of the projected equilibrium  
458 warming  $\Delta T$ , these equations still hold.

459

460 Finally we note that the total system feedback  $\lambda$  can be decomposed into the additive effect of  
461 multiple feedbacks in the system of strengths  $\lambda_i$ ,

462

$$463 \quad \lambda = \sum \lambda_i \quad (5)$$

464

465 These feedbacks represent how the TOA radiation balance is altered as the climate warms by  
466 forced changes in identified radiatively active constituents of the climate system. In this study these  
467 are represented as six feedback components: the Planck feedback, combined water vapor and  
468 lapse rate feedback, total cloud feedback, surface albedo feedback, stratospheric feedback and an  
469 additional atmospheric composition feedback. These individual feedback components are  
470 elaborated in section 3, where evidence is presented to constrain each of them (sections 3.3, 3.4;

471 Table 1). Other process evidence is presented (section 3.5) which constrains the total,  $\lambda$ .  
 472 Finally, so-called “emergent-constraint” studies are discussed (section 3.6) which tie  $S$  to some  
 473 observable in the present-day climate, thereby constraining  $\lambda$  and  $S$ . For reasons discussed later  
 474 however they are not used in our Baseline calculation, but are explored via a sensitivity test.  
 475

476 The other evidence used (sections 4, 5) comes from past climate changes and typically is  
 477 interpreted via eqs. ( 2, 3) in previous climate sensitivity studies. These have typically  
 478 assumed that the equations apply to any relevant climate change with universal values of  $\lambda$  and  $S$ ,  
 479 provided that the same feedbacks are counted therein (cf. eq. ( 5)). We will likewise apply  
 480 these equations simultaneously to different past climate change scenarios, leading to a set of  
 481 relationships shown graphically in Figure 2 (which offers a picture of our overall model, in  
 482 particular its dependence structure; see section 2.4.2 for more information).  
 483

484 Recent work however has shown that effective  $\lambda$  (the value that satisfies eq. ( 2) for some  
 485 climate-change scenario) can vary significantly across scenarios even when the same feedbacks  
 486 are nominally operating. All measurements relevant to climate sensitivity come from the recent  
 487 historical period (during which internal variability may play a large role and the climate is far out of  
 488 equilibrium; section 4) or from proxy reconstructions of past climate equilibria (during which the  
 489 climate may have been quite different to that of the reference scenario; section 5). Thus, possible  
 490 variations in the apparent  $\lambda$  during those time periods must be accounted for. Two particular issues  
 491 are recognized. First, feedbacks can change strength in different climate states due to direct  
 492 dependence on global temperature or indirect dependence (e.g. via snow or ice cover), or other  
 493 differences in the earth system (e.g., topography). Second, the net outgoing radiation  $\Delta N$  can  
 494 depend not only on the global mean surface temperature but also on its geographic pattern  $\Delta T'$ ,  
 495 leading to an apparent dependence of  $\lambda$  on  $\Delta T'$  when applying eq. ( 2). Such pattern variations  
 496 can arise either because of heterogeneous radiative forcings, lag-dependent responses to  
 497 forcings, or unforced variability. To use such observations to constrain our  $S$  and  $\lambda$ , it is important  
 498 to account for these effects. Note that these effects are distinct from atmospheric “adjustments” to  
 499 applied radiative forcings (Sherwood et al., 2015), which scale with the forcing and are included as  
 500 part of the effective radiative forcing  $\Delta F$ .  
 501

502 We account for impacts on  $\lambda$  by defining an additive correction  $\Delta\lambda$  for each past climate change  
 503 representing the difference between its apparent  $\lambda$  and the “true”  $\lambda$  defined by our reference  
 504 scenario. For simplicity we define these corrections to subsume both forcing-related and unforced  
 505 variations, so that henceforth  $V=0$ . Equation ( 2) then becomes  
 506

$$\Delta N = \Delta F + (\lambda - \Delta\lambda)\Delta T. \quad ( 6)$$

507  
 508  
 509 where  $\lambda$  is the “true” value we want to estimate. From the chain rule, having assigned to  $\Delta\lambda$  two  
 510 components, we obtain:  
 511

$$\begin{aligned} \Delta\lambda &= \frac{\partial\lambda}{\partial T} \Delta T + \frac{\partial\lambda}{\partial T'(x)} \Delta T'(x) \\ &= \Delta\lambda_{state} + \Delta\lambda_{pattern}. \end{aligned} \quad ( 7)$$

512  
 513  
 514  
 515  
 516 **State dependence.** The first term represents state dependence: the concept that the feedbacks in  
 517 a glacial climate, for example, might not remain the same strength over the next century. Ice-  
 518 albedo feedback for example has long been expected to be climate sensitive (Budyko, 1969;

519 Sellers, 1969), and some studies have found strong sensitivity of cloud feedbacks (Caballero and  
520 Huber, 2013). The simplest parameterization of this is to add a quadratic dependence of net  
521 outgoing radiation on  $\Delta T$ , which yields a linear dependence of total feedback  $\lambda$ ,

522

$$523 \quad \Delta\lambda_{\text{state}} = 2 \alpha \Delta T$$

524

525 There are however reasons to expect changes could be nonlinear (for example discontinuous  
526 changes in cloud feedbacks when ice sheets disappear) so this formulation will not always be used  
527 (see section 5). State-dependence corrections are made only for paleoclimate evidence, and state  
528 dependence of  $\Delta F_{2\times\text{CO}_2}$  is subsumed into that of  $\lambda$ .

529

530 **Pattern Effects.** The second term represents the “pattern effect” and expresses the possibility that  
531 different patterns of warming will trigger different radiative responses. The pattern effect is  
532 significant whenever (a) the pattern of temperature change differs from that in the reference  
533 scenario *and* (b) this difference in pattern is radiatively significant, i.e., alters the global mean top-  
534 of-atmosphere net radiation. Such patterns can arise either due to non-CO<sub>2</sub> forcings, lags in  
535 response, or unforced variability. In section 4.2, the possible existence of a pattern effect arising  
536 from transient warming patterns that do not resemble the eventual equilibrium response is  
537 discussed further. Pattern effects may also complicate the comparison of estimates derived from  
538 proxy reconstructions of past equilibria, if the resulting SST patterns differ from those of the  
539 reference scenario. However, in the absence of reliable reconstructions of past warming patterns  
540 and a dearth of existing literature addressing this, here we do not explicitly consider paleoclimate  
541 pattern effects. We note that the concept of forcing “efficacy” (i.e., Hansen et al., 2005; Winton et  
542 al., 2010; Marvel et al., 2016; Stahl et al., 2019), in which one unit of radiative forcing produces a  
543 different temperature response depending on where, geographically, it is applied, can be attributed  
544 to a pattern effect (e.g., Rose et al., 2014) or to a forcing adjustment. Our estimated historical and  
545 paleo forcings  $\Delta F$  will include uncertainties from adjustment/efficacy effects.

546

547 **Time Scale.** Finally, we note that any definition of planetary sensitivity depends on the timescale  
548 considered. Our  $S$  incorporates only feedbacks acting on time scales of order a century. Traditional  
549 ECS allows for more complete equilibration of the system, albeit with some feedbacks explicitly  
550 excluded (see section 2.1). In this report we assume that ECS and  $S$  are related via

551

$$552 \quad \text{ECS} = (1+\zeta) S. \quad (8)$$

553

554 See section 5.2.3 for more information. *Earth System Sensitivity*, by contrast, reflects the slower  
555 feedback processes such as changes to the carbon cycle and land ice. Due to the lack of  
556 information on short temporal scales, most paleoclimate reconstructions necessarily incorporate  
557 the effects of these slow feedbacks. The difference between ESS and  $S$  or ECS is not relevant to  
558 the analyses in sections 3 and 4, but is discussed further in section 5.3.

559

## 560 **2.3 Statistical method: summary**

561

562

563 To obtain *probability distributions* of the various quantities introduced and mathematically linked in  
564 section 2.2, we adopt the Bayesian interpretation of probability, which describes our uncertain  
565 beliefs concerning facts that are not intrinsically random but about which our knowledge is

566 uncertain (e.g., Bernardo and Smith, 1994). The Bayesian approach has been adopted in many  
 567 past studies inferring climate sensitivity from historical or paleoclimate data (see sections 4 and 5),  
 568 and is used for other climate-relevant problems such as data assimilation (Law and Stuart, 2012),  
 569 remote sensing (Evans et al., 1995), and reconstruction of past temperatures (Tingley and  
 570 Huybers, 2010), among others.

571  
 572 The basic expression of Bayes' rule for the case of unknown variables is  
 573

$$574 \quad p(\Phi|E) = \frac{p(E|\Phi)p(\Phi)}{p(E)} \quad (9)$$

575  
 576 where  $\Phi$  is a vector of *variables* (in our case feedbacks  $\lambda_i$  and total  $\lambda$ , forcings, temperature  
 577 changes, parameters representing  $\Delta\lambda$ 's, and  $S$ ), and  $E$  represents some *evidence* about these  
 578 variables.  $p(\Phi|E)$  is our sought-for *posterior probability density* of  $\Phi$  given (conditional on)  $E$ , i.e.,  
 579 the joint PDF of all the variables considering the evidence. On the right-hand side,  $p(E|\Phi)$ , the  
 580 *likelihood*, measures the probability of the evidence  $E$  for any given  $\Phi$  and is what quantifies the  
 581 constraint offered by the evidence.  $p(\Phi)$  is our *prior* for  $\Phi$ , that is, the PDF we would assign to  $\Phi$  in  
 582 the absence of  $E$ .  $p(E)$ , the overall probability of  $E$ , is essentially a normalization constant. A key  
 583 insight is that a PDF can never be determined by evidence alone, but begins with one's prior  
 584 expectations  $p(\Phi)$  which are then modified by the evidence. The PDF is small for  $\Phi$  that are judged  
 585 implausible at the outset (small prior) or unlikely to have led to the observed evidence (small  
 586 likelihood). If the evidence is strong enough to restrict values to a sufficiently narrow range, the  
 587 prior becomes practically irrelevant; this is typical for standard scientific measurements and the  
 588 prior is usually unexamined. It is unfortunately not the case for climate sensitivity, so we need to  
 589 pay attention to the prior.

590  
 591 Because of the structure of our problem (in particular that  $\Delta F_{2\times\text{CO}_2}$  is relatively well known and  
 592 many conditional independencies are expected among the variables, see section 2.4.2), the Bayes  
 593 result ( 9) can approximately be written in terms of  $\lambda$  alone:

$$594 \quad p(\lambda | E) \propto p(\lambda | E_{\text{proc}}) p(E_{\text{hist}} | \lambda) p(E_{\text{paleo}} | \lambda) \quad (10)$$

595  
 596 and a similar equation can be written for  $S$ . Thus the PDF of either sensitivity measure is  
 597 approximately proportional to the product of three components, one for each of our lines of  
 598 evidence, where  $E_{\text{proc}}$  is the process evidence and so on. The first term on the right-hand side of  
 599 eq. ( 10) is the PDF given only our process understanding and an assumed prior on the  
 600 feedbacks; this is estimated in section 3. The second and third terms are *marginal* likelihoods of  
 601 the historical and paleo evidence as functions of the sensitivity measure, worked out (sections 4-5)  
 602 by directly computing the probability of our best-estimate warming as a function of all variables  
 603 using the equations given in section 2.1. The posterior PDFs will be shown in section 7 (and  
 604 employ a fully accurate calculation viz. eq. ( 9) with full likelihoods rather than marginal ones;  
 605 see section 2.4). Although eq. ( 10) is not exact, it is a very good approximation helpful in  
 606 understanding results.  
 607

608  
 609 Importantly each term in eq. ( 10) is computed using a model (cf. section 2.6), and involves  
 610 judgments about structural uncertainty including limitations of the model. Our goal is for each term  
 611 to represent fully educated and reasonable beliefs. In sections 3-5 we will sometimes present a  
 612 range of calculations and evidence and then assert a quantitative likelihood informed by the totality  
 613 of this evidence and background knowledge. This will to some extent be unavoidably subjective.

614  
615 A key assumption behind the multiplication in eq. ( 10) (also made in the fully accurate  
616 calculation) is that the lines of evidence are *independent*, which we assume for our Baseline  
617 calculation. For example, this means that learning the true historical aerosol radiative forcing would  
618 not alter our interpretation of the paleo or process evidence, and so on for other uncertainties. The  
619 plausibility of this assumption and consequences of relaxing it are explored in different ways in  
620 sections 6 and 7.

621  
622 Many past studies (see sections 3-5) have produced PDFs of  $S$  based on a single line of evidence  
623 represented by one likelihood term in eq. ( 10). One might think that if two such likelihoods from  
624 different evidence look different, it means there is some inconsistency or problem in the way  
625 evidence is being interpreted. This is a misconception. Suppose one line of evidence demonstrates  
626  $S$  is above 3 K and the other that it is between 0 and 4 K; each by itself would yield a very different  
627 PDF, but together, they simply say  $S$  must be between 3 K and 4 K. This is embodied in eq. ( 10).  
628 The difference in ranges is no reason to question either line of evidence so long as there is  
629 reasonable overlap. This point will be revisited in section 8 when discussing what turns out to be  
630 strong similarity among our lines of evidence.

631  
632 In general, as discussed above, posterior PDFs depend on a (multivariate) prior. This prior is  
633 placed on all variables in the system and must obey the model equations (section 2.2) which force  
634 the beliefs it expresses about different variables to be consistent. In practice one begins with  
635 independent variables (in our case the individual feedbacks  $\lambda_i$ ,  $\Delta F_{2\times\text{CO}_2}$ , and for each past climate  
636 change the forcing  $\Delta F$ , observational error for  $\Delta T$ , and parameters for  $\Delta\lambda$ ; see sections 4 and  
637 section 5). A prior on the dependent variables (i.e., the so-called *prior predictive distribution*), such  
638 as  $\lambda$  and  $S$ , is then determined by the independent-variable prior and the model. In cases where  
639 one has prior knowledge about a dependent variable  $X$ , the prior on the independent variables can  
640 be adjusted so that the prior predictive distribution of  $X$  reflects this (see e.g., Wang et al., 2018).

641  
642 For each independent variable except the  $\lambda_i$ , we specify a marginal prior PDF by expert judgment  
643 using available evidence, discussed in the relevant section 3-5. This is typical of past Bayesian  
644 studies. The knowledge used to specify the prior for each variable is specific to that variable and  
645 not used elsewhere (this is important for the historical forcing PDF, section 4.1.1). For the  $\lambda_i$ , we  
646 explicitly consider a likelihood of each feedback's evidence  $E_i$  and a separate prior; i.e, the PDF of  
647  $\lambda_i$  is  $p(\lambda_i)p(E_i|\lambda_i)$ . All of these prior PDFs adjust when the evidence is considered, resulting in  
648 posterior PDFs.

649  
650 Our baseline choice for the prior  $p(\lambda_i)$ , which is consistent with past work on estimating feedbacks  
651 components with which we are familiar, is uniform (over negative and positive values) and  
652 independent between feedbacks (i.e., learning information about one feedback would not alter our  
653 beliefs about others in the absence of other information on  $S$ ; see section 7.2 for more discussion).  
654 From eq. ( 5), this implies a prior on  $\lambda$  that is also uniform across positive and negative values.  
655 Thus we don't rule out an unstable climate *a priori*. An unstable climate is however ruled out by  
656 non-process evidence (i.e., the length and stability of Earth's geologic record). For efficiency, at the  
657 outset we eliminate from our numerical calculations individual  $\lambda_i$  for which the process likelihood is  
658 less than  $10^{-10}$ . Note that if the  $\lambda_i$  priors are restricted—e.g., a broad Gaussian rather than  
659 uniform—results are essentially unaffected , since values far away from zero are ruled out by  
660 evidence.

661  
662 We also consider a different multivariate prior PDF, specified in such a way as to induce a prior

663 predictive distribution on  $S$  (via eq. 4) that is uniform from near 0 up to 20 K. This assigns high  
664 prior belief to combinations of  $\lambda_i$  that happen to sum to small negative  $\lambda$ , and zero belief to  
665 combinations summing to positive  $\lambda$  (for which  $S$  is undefined). Implementation of priors is further  
666 discussed in section 2.4.3, and issues concerning the choice of prior are discussed in section 7.2.  
667

## 668 2.4 Statistical method: Further information

### 669 2.4.1 Introduction to Bayesian Inference modelling

670  
671 Bayes' Theorem arises as a consequence of the laws of probability. Considering all possible  $\Phi$  and  
672 all  $E$  that could have eventuated, the joint density (or probability, or PDF) of  $E$  and  $\Phi$  of the real  
673 world,  $p(E, \Phi)$ , can be decomposed in two different ways via  
674

$$675 p(E, \Phi) = p(\Phi|E)p(E) = p(E|\Phi)p(\Phi)$$

676  
677 which immediately leads to eq. (9).

678  
679 The likelihood  $p(E|\Phi)$  is determined by the inference model, which takes the variables as an input  
680 and predicts what would be observed as a consequence of these variables. It is often a source of  
681 confusion. Although expressed as a probability (of  $E$ ), once  $E$  is known,  $p(E|\Phi)$  is best thought of  
682 as a relative measure of the consistency of the evidence with each value of  $\Phi$ , according to our  
683 inference model. Low likelihoods indicate a  $\Phi$  that would be unlikely to give rise to the evidence  
684 that was seen, and if the likelihood is low enough, we would say this  $\Phi$  is inconsistent with that  
685 evidence. Bayes' Theorem says that the probability of  $\Phi$  given evidence is determined by two  
686 things: the a priori plausibility of  $\Phi$ , and the consistency of  $\Phi$  with the evidence. Strictly speaking,  
687 "evidence"  $E$  should be observations of the real world. However in this assessment (section 3 in  
688 particular) we will also selectively consider as evidence the emergent behavior of numerical  
689 simulations of processes (for example large-eddy simulations of cloud systems), where the  
690 numerical model is informed by, and tested against, observations not used elsewhere in the  
691 assessment.

692  
693 The roles of the prior and likelihood are most simply illustrated by an example of a test for a rare  
694 disease. If the test correctly identifies both diseased and non-diseased patients 95% of the time,  
695 but only 1% of people tested carry the disease, then a patient who tests positive still only has  
696 ~16% probability of carrying the disease. This is because even though the likelihood  $p(E|\Phi)$  of the  
697 positive test result is high (0.95) under the hypothesis that the patient is diseased ( $\Phi=1$ ), and low  
698 (5%) under no-disease ( $\Phi=0$ ), the very low prior  $p(\Phi=1) = 0.01$  due to the rarity of the disease  
699 renders a low 0.16 posterior  $p(\Phi=1|E)$  of disease. This may be obtained from eq. (9) noting  
700 that  $p(E \text{ positive}) = 0.01 \times 0.95 + 0.99 \times 0.05$  (equivalently one can reason that out of 10,000  
701 patients, 100 would have the disease, 95 of whom would test positive; but of the 9,900 who do not  
702 have the disease, 5% or 495 would wrongly test positive, such that only 16% of those testing  
703 positive are actually diseased). This example illustrates that prior information or beliefs can have a  
704 powerful influence on outcomes, a point that has been emphasized in the context of inferring ECS  
705 from the historical record (see Bindoff et al., 2013; Lewis, 2014).

706  
707 While the above example is based on discrete (binary)  $\Phi$ , in this assessment all variables are  
708 continuous. Hence probabilities are expressed as densities or continuous distributions in a real

709 space. To illustrate this case, consider that one has a thermometer with a Gaussian-distributed  
710 error of standard deviation  $2^{\circ}\text{C}$ , and measures the temperature  $T$  of some fresh water and obtains  
711  $1.5^{\circ}\text{C}$ . Now since we know the water is liquid, the temperature must *a priori* lie between  $0\text{--}100^{\circ}\text{C}$ . If  
712 our prior  $p(T)$  is uniform (all unit intervals of Celsius temperature equally likely) within that range  
713 and zero outside, our likelihood  $p(\text{obs} | T)$  is normally distributed about  $1.5^{\circ}\text{C}$ , but the posterior PDF  
714 is truncated with no weight on negative temperatures. Thus the *maximum-likelihood* temperature  
715 (the one most consistent with the evidence) is  $1.5^{\circ}\text{C}$ —but the *expectation value* (the mean of the  
716 PDF, or the average true temperature if this situation occurred many times) is higher at  $2.27^{\circ}\text{C}$ .  
717 One could also imagine a highly non-uniform prior within  $0\text{--}100^{\circ}\text{C}$ , for instance if the water were  
718 known to be in the Arctic region. In this case  $T$  would be highly likely *a priori* to be near the freezing  
719 point, and its expectation value given the measurement might even be lower than the  
720 measurement. Other priors could also be possible, based on analogous past experience or any  
721 other line of reasoning.

722  
723 The role of multiple lines of evidence, important for our assessment, is also clarified by a Bayesian  
724 approach. If, in the above example, we had two independent measurements with the same  
725 Gaussian uncertainty each returning  $1.5^{\circ}\text{C}$ , we would multiply the two likelihoods and renormalize,  
726 obtaining a new likelihood with a standard deviation of  $1.4^{\circ}\text{C}$  (which could be combined with the  
727 same prior to get a new PDF). This independence assumption would be justified if the second  
728 observation came from a different technology, for example infrared radiometry. But if it came from  
729 the same thermometer used again, we would expect the same error both times and the new  
730 likelihood and PDF would be unchanged. If the second observation came from another  
731 thermometer by the same manufacturer, we would have to delve into the reasons for thermometer  
732 error to decide how independent we expect the two measurements to be. These issues are highly  
733 relevant to this assessment and are discussed in section 6.

734  
735 The final generalization required is that our problem is multivariate. In section 2.4.2 we describe in  
736 more detail the multivariate problem solved in this assessment.

737

## 738 **2.4.2 Description of methods and calculations.**

739 Following eq. ( 9 ) the most general approach for a multivariate system, after specifying a  
740 prior, would be to calculate the likelihood of the entirety of evidence  $E$ , as a function of the full set  
741 of model variables  $\Phi$  (of which there are 15 if we treat six distinct feedbacks,  $\lambda$ ,  $\Delta F_{2\times\text{CO}_2}$ ,  $S$ , and  
742 three pairs of  $\Delta T$  and  $\Delta F$ —one historical and two paleoclimate—see sections 3 and 5). Calculating  
743 a 15-dimensional likelihood function in this way is computationally inefficient, and moreover is not  
744 very helpful conceptually. Fortunately we can simplify and better understand the problem by  
745 considering more carefully the relationships between variables.

746

747 These relationships are illustrated graphically in Fig. 2, separated into three broad lines of  
748 evidence. All quantities in eqs. ( 3- 5) are unknown (random) variables characterized by  
749 PDFs, shown as circles in this figure. So the only things “known” before priors are placed on the  
750 variables are the evidence (shown by boxes); the equations linking the variables; and the  
751 relationships between these variables and the evidence. Note that while many previous ECS  
752 studies have taken  $\Delta F_{2\times\text{CO}_2}$  as a known constant, we consider it as uncertain, and therefore  $\lambda$  and  $S$   
753 are not uniquely related—though in practice the uncertainty in  $\Delta F_{2\times\text{CO}_2}$  is relatively small and  $\lambda$  and  
754  $S$  are nearly reciprocal.

755



756 Fig. 2 shows the dependence in the inference model, in which individual feedbacks combine to  
 757 determine  $\lambda$ , which then determines (together with  $\Delta F_{2\times\text{CO}_2}$ )  $S$  and (together with forcings) the  
 758 magnitude of forced responses. The arrows indicate direct causality, where a (“child”) node value  
 759 is determined by the (“parent”) variables upstream that point to it. This has strict implications for  
 760 the conditional independence of variables inherent in the joint distribution  $p(\Phi)$ —most importantly,  
 761 that any variable is conditionally independent of all others that are not its descendants, given its  
 762 parents (see e.g., Pearl 1988). The Bayesian inference process can work backward, where  
 763 information on a child tells us about its parent(s), and information from multiple children is  
 764 independent if there are no direct links in the diagram between the children.

765  
 766 A first simplification therefore is that the evidence consists of a set of components (boxes in Fig.  
 767 2) which we suppose to be *conditionally independent* given  $\Phi$ . In general we suppose the  
 768 remaining uncertainties in  $E$ , once  $\Phi$  is known, arise from instrumental and other errors that are  
 769 unrelated between lines of evidence; possible violations of independence will be revisited later in  
 770 the assessment. The likelihood components can be collected into lines of evidence (for example  
 771 the three shown by colors in Fig. 2) and, based on this independence ansatz, the likelihood of  
 772 all evidence  $E$  can be written:

$$773 \quad p(E | \Phi) = p(E_{\text{proc}}|\Phi)p(E_{\text{hist}}|\Phi)p(E_{\text{paleo}}|\Phi), \quad (11)$$

774  
 775 where  $p(E_{\text{proc}}|\Phi)$  is termed the “process likelihood,” which isolates the impact of process evidence,  
 776 and so on for the other two. The multivariate PDF of  $\Phi$  follows from inserting eqs. (11) into (9);  
 777 to obtain the marginal posterior PDF of  $S$ ,  $p(S | E)$  (or any other particular variable) would  
 778 require integrating that multivariate PDF over all variables in  $\Phi$  other than  $S$ .

779  
 780 A further simplification however is that in our inference model, each evidence line directly depends  
 781 only on the most immediate model variable(s), not the entire  $\Phi$ . For example, once  $\lambda$  and historical  
 782  $\Delta F$  are specified, the historical warming  $\Delta T$  does not depend on paleoclimate changes or individual  
 783 feedbacks, a further statement of conditional independence. This means that the historical  
 784 likelihood  $p(E_{\text{hist}}|\Phi)$  can be written as a function of  $\lambda$  and  $\Delta F_{2\times\text{CO}_2}$  alone, e.g.,  $p(E_{\text{hist}}|\lambda, \Delta F_{2\times\text{CO}_2})$ . The  
 785 same can be done for the paleo evidence. This motivates an expression analogous to eq. (9)  
 786 for the total likelihood or PDF of just the variables of interest,  $\lambda$  or  $S$ , which we develop here for  
 787 better understanding of the approach.

788  
 789 It is not possible however to simplify the entire process likelihood in a similar way to the historical  
 790 and paleo likelihoods as above. This is because the primary part of this evidence consists of  
 791 multiple pieces  $E_i$  pertaining to individual feedbacks  $i$ , and these cannot be written as a function of  
 792  $\lambda$ ; hence we cannot directly write  $p(E_{\text{proc}}|\lambda, \Delta F_{2\times\text{CO}_2})$ . Each  $E_i$  can however be written as a function of  
 793 its parent feedback value  $\lambda_i$  alone which is again a great simplification. These feedback values are  
 794 the *independent variables* in our inference model (those with no parent variables). Starting from  
 795 these, the PDF of each feedback, given its direct evidence  $E_i$  only, is

$$796 \quad p(\lambda_i | E_i) = p(E_i | \lambda_i) p(\lambda_i) / p(E_i). \quad (12)$$

797  
 798 where  $p(\lambda_i)$  is a prior PDF for  $\lambda_i$ . The posterior PDF of the total  $\lambda$  given all individual-feedback  
 799 evidence  $E_i$  is an integral over these component feedbacks:

$$800 \quad p(\lambda | E_1, \dots, E_n) \propto \int \prod p(\lambda_i | E_i) \delta(\lambda - \sum \lambda_i) d\lambda_1 d\lambda_2 \dots d\lambda_n \quad (13)$$

805 where hereafter, for clarity, we omit normalization constants. In the special case of Gaussian  
 806 distributions, which result from the priors and likelihoods employed in section 3, this integral  
 807 produces another Gaussian whose mean and variance are simply the sums of those of the  
 808 components (see e.g., Ross 2019).

809  
 810 There is additional process evidence  $E_\lambda$ , from “emergent constraint” approaches, that depends on  
 811 the total  $\lambda$ ; i.e.,  $E_{\text{proc}} = \{E_i, \dots, E_n, E_\lambda\}$ . The PDF of  $\lambda$  given all process evidence, if both types are  
 812 independent, is the product of the component-derived PDF (eq. 13) and the likelihood of this  
 813 additional evidence:

$$814 \quad p(\lambda | E_{\text{proc}}) \propto p(\lambda | E_i, \dots, E_n) p(E_\lambda | \lambda). \quad (14)$$

815  
 816 (However in part because of dependence concerns, this evidence is only used in a sensitivity test,  
 817 see section 3). The historical and paleo evidence depends on  $\lambda$  and  $\Delta F_{2xCO_2}$  (denoted  $F$  in eqs. (15–17) for brevity). We assume (see section 3.4) that  $\lambda$  and  $F$  are independent *a priori*, so that

$$818 \quad p(\lambda, F | E_{\text{proc}}) = p(\lambda | E_{\text{proc}}) p(F). \quad (15)$$

819  
 820 This can be combined with the other lines of evidence to yield:

$$821 \quad p(\lambda, F | E) \propto p(\lambda, F | E_{\text{proc}}) p(E_{\text{hist}} | \lambda, F) p(E_{\text{paleo}} | \lambda, F). \quad (16)$$

822  
 823 Integrating eq. (16) over  $F$  yields a marginal PDF of  $\lambda$ . Also, using eq. (4), the marginal PDF  
 824 of  $S$  could be obtained by integrating over  $\lambda$  and  $F$ :

$$825 \quad p(S | E) \propto \int p(F) p(\lambda', F | E) \delta(S - F/\lambda') (\partial S / \partial F)^{-1} (\partial S / \partial \lambda)^{-1} dF d\lambda' \quad (17)$$

826  
 827 where primes denote integration variables. In practice,  $\Delta F_{2xCO_2}$  contributes very little to the  
 828 uncertainty in historical or paleo forcings, and therefore plays a weak role in those likelihoods. If  
 829 the interdependence among likelihoods arising from this small role is neglected, the above  
 830 integrals over  $\Delta F_{2xCO_2}$  could be performed separately for each line of evidence rather than over the  
 831 entirety, yielding eq. (10) given earlier or an equivalent equation for  $S$ . Note that calculations  
 832 shown in this assessment do not make this approximation. Equation (10) or its  $S$  equivalent  
 833 resemble the basic equation used in past ECS studies on the historical and/or paleo records,  
 834 except that the process PDF  $p(\lambda | E_{\text{proc}})$  or  $p(S | E_{\text{proc}})$  takes the place usually occupied by the prior  
 835 on ECS or  $\lambda$ .

836  
 837 So far eq. (16) shows likelihoods for historical and paleo evidence only. The process PDF (eq.  
 838 14) can be written as the product of a process marginal likelihood  $p(E_{\text{proc}} | \lambda)$  and a *prior predictive*  
 839 *distribution* (PPD),  $p(\lambda)$ , which is the prior PDF on  $\lambda$  induced by those placed on the independent  
 840 variables upstream. An analogous product can be written for  $S$ . Either PPD can be calculated from  
 841 eqs. (12–17) by setting the likelihoods to unity, since it is just the predicted distribution of  $\lambda$  and  
 842  $S$  with no evidence. The marginal process likelihood is then the ratio of the process PDF to this  
 843 PPD. Calculating this likelihood thus requires integrating over all possible combinations of the  $\lambda_i$   
 844 (i.e., their joint distribution) weighted by their prior probabilities. This is because an individual  
 845 feedback value/evidence  $E_i$  cannot be predicted from the sum  $\lambda$  alone; its likelihood of occurrence  
 846 for a given total depends on the probabilities (hence priors) of all of the feedbacks. Hence the  
 847 marginal process likelihood vs.  $\lambda$  or  $S$  is not independent of the prior the way the other likelihoods  
 848

853 are: it changes each time the prior is changed.

854

855 There is in general no closed form solution to eqs. ( 13–17) and therefore we use a Monte Carlo  
856 sampling approach to compute the solution. This is described further in section 2.4.4. This  
857 approach is fully consistent with eqs. ( 13–17) but approaches the problem more directly via eq.  
858 ( 11).

859

### 860 **2.4.3 Specification of priors and novel aspects of our approach**

861

862 As mentioned in section 2.3, prior PDFs must be placed on all independent variables, and are  
863 propagated to the dependent variables (such as  $\lambda$  and  $S$ ) via the model equations. For each of the  
864 independent variables except the  $\lambda_i$ , the prior PDF is specified by expert judgment using the  
865 available evidence about that quantity, without considering any other lines of evidence. These  
866 expert priors are given in the appropriate sections and are crucial in determining the historical and  
867 paleo likelihoods. Note that PDFs of these and other variables change once all the evidence is  
868 propagated through the model. For example, if historical warming turns out to be weaker than  
869 would be expected based on the other lines of evidence, then our posterior PDF of  $S$  shifts  
870 downward from what it would have been with only the other evidence—but at the same time, our  
871 posterior PDF of the historical  $\Delta F$  also shifts downward relative to what we expected *a priori*.  
872 These revised, posterior PDFs will not be presented except those of  $S$  and the historical forcing  
873  $\Delta F$ .

874

875 Many previous studies have used past climate changes to constrain climate sensitivity using  
876 Bayesian methods (e.g., Aldrin et al., 2012; Johannsen et al., 2015; 2018, Skeie et al., 2014;  
877 2018), and so had to specify priors. Such studies mostly aimed to constrain  $S$  without  
878 incorporating the process knowledge exploited here, instead fitting inference models formulated  
879 with  $S$  or  $\lambda$  as an independent variable. As such, they required prior PDFs for  $S$  (which were  
880 typically uniform in  $S$  or peaked at  $S$  values somewhere within the 1.5-4.5 K range). Due to the use  
881 of a different inference model, the prior on  $S$  in this assessment is nominally based on less  
882 information and hence not fully equivalent to those in the past Bayesian ECS studies. This and  
883 other issues of how to interpret the priors are taken up in section 7.2.

884

### 885 **2.4.4 Calculation of likelihoods and sampling method**

886

887 Implementation of the Bayesian updating generally follows the principles described in Liu (2004), in  
888 which we sample from our prior over  $\Phi$  and weight each instance in the sample according to the  
889 likelihood  $P(E|\Phi)$ . The weighted ensemble is then an approximation to the posterior PDF, and can  
890 be analyzed and presented as desired (e.g., in terms of the mean/expectation and credible  
891 intervals) via relationships such as expectation  $E[\Phi|E] = \sum(w_j \Phi_j) / \sum(w_j)$  where  $\sum$  denotes a sum  
892 over all instances  $\Phi_j$  from  $\Phi$  and  $w_j$  is the weight. This approach can also be viewed as a specific  
893 form of Importance Sampling (Gelman et al., 2013) in which the prior is used as an initial ‘proposal’  
894 distribution from which samples are drawn and subsequently weighted to estimate the target  
895 distribution.

896

897 To create the sample, we begin by sampling the independent variables according to their priors  
898 (e.g., uniform sample distribution for a uniform prior), and then use the inference model equations

899 to calculate the values of each dependent variable (such as  $S$ ) and the model outputs for each  
 900 instance in the sample. This yields a sample population approximating the PPD for all variables in  
 901  $\Phi$ . Next, a weight  $w_j$  for each instance  $j$  is computed from the global likelihood function (which is a  
 902 product of local likelihoods, cf. eq. ( 11). Finally, the posterior PDF is approximated by the  
 903 histogram of the weighted sample (see below).

904  
 905 For the individual-feedback process evidence (see section 3), the likelihood for each feedback  
 906 component  $i$  is represented as a Gaussian function with mean  $\mu_i$  and standard deviation  $\sigma_i$ . Each  
 907 sample instance  $j$  is accordingly given a likelihood weight for  $\lambda_{ij}$  equal to  $G(\lambda_{ij}, \mu_i, \sigma_i)$  where  $\lambda_{ij}$  is the  
 908  $i_{th}$  feedback value of the  $j_{th}$  instance in the sample, and  $G(x, \mu, \sigma)$  is defined as the Gaussian  $N(\mu, \sigma)$   
 909 function evaluated at  $x$ . The weights for the six feedbacks are multiplied to give the total likelihood  
 910 weight for the individual-feedback evidence. In the baseline case with a prior uniform in  $\lambda_i$ , the  
 911 posterior after updating by this likelihood thus approximates the anticipated Gaussian  $N(\mu_i, \sigma_i)$ ,  
 912 although we do not explicitly take advantage of this relationship within the algorithm, in order to  
 913 allow full generality. Similarly, an “emergent constraint” likelihood is specified in terms of a  
 914 Gaussian in total  $\lambda$ , evaluated  $G(\lambda_j, \mu_\lambda, \sigma_\lambda)$ .

915  
 916 For the observed temperature change evidence (see sections 4 and 5), we consider a forward  
 917 model in the basic form (cf. eq. 3):

$$918 \quad \Delta T = f(\Phi')$$

920  
 921 where the predicted temperature change  $\Delta T$  is a function of the other model variables  $\Phi'$ . The  
 922 observed temperature change  $\Delta T_{obs}$ , which includes an uncertainty  $\sigma_e$  due to measurement error  
 923 and unforced variability, is interpreted as giving rise to a likelihood which takes the Gaussian form  
 924  $N(\Delta T, \sigma_e)$  (Annan and Hargreaves, 2020). Thus the likelihood assigned to any  $\Phi'$  is  $G(\Delta T, \Delta T_{obs},$   
 925  $\sigma_e)$ , which is the probability of the observed warming for a given  $\Delta T=f(\Phi')$ . This value is maximized  
 926 when  $\Delta T$  is equal to  $\Delta T_{obs}$  and drops off rapidly as the difference between  $\Delta T$  and  $\Delta T_{obs}$  becomes  
 927 large compared to  $\sigma_e$ . The exact forward models used will differ from ( 3) due to additional terms  
 928 as previously mentioned, and are given in sections 4 and 5.

929  
 930 Likelihood weights for process (excluding emergent-constraint), emergent-constraint, historical,  
 931 and paleoclimate evidence (separately for cold and warm periods) are calculated for each  
 932 instance. These weights (or a subset thereof) are then multiplied together to give a single  
 933 likelihood weight  $w$  for each member of the sample.

934  
 935 The posterior PDF for  $\Phi$  can be calculated from the weighted sample distribution; marginal PDFs  
 936 for variable subsets are calculated from the marginal sample distributions. For example, a  
 937 posterior PDF for  $S$  is calculated as the histogram of  $S$  in the sample (i.e, the PPD), weighted by  
 938 the corresponding likelihood weights—i.e.,  $p(S | E) \propto \sum_{j \in Q} w_j$ , where the set  $Q$  contains all  
 939 instances  $j$  whose  $S_j$  falls within a histogram bin centered on  $S$ —with normalization. Posterior  
 940 PDFs for any other variable in  $\Phi$  are calculated similarly. The marginal likelihood function for any  
 941 variable (e.g.,  $S$ ) is just the average weight  $w$  from the same histogram. Hence the marginal  
 942 likelihood is equal to the PDF divided by the PPD.

943  
 944 Various approximations are made in the sampling calculations to make them less computationally  
 945 expensive. The Baseline calculation initially samples each feedback component uniformly and  
 946 independently over the range  $U(-10, 10)$  (see Figure 7.2). We also use an alternative prior which is  
 947 calculated by weighting samples from the Baseline prior to give a PPD for  $S$  which is uniform from

948 near zero to 20 K. This does not include zero because the Baseline prior covers a finite range  $U(-$   
949  $10,10)$ . When calculating the posterior, to avoid wasted computational effort, we restrict the initial  
950 sample to absolute values for each feedback  $\lambda_i$  within a six standard-deviation range of the  
951 likelihood function for that feedback. This does not affect the posterior PDF because the likelihood  
952 is effectively zero outside this range. The posterior calculation in section 7.2 with a uniform-S PPD  
953 uses a weighted version of an equivalent sample (and so also makes this approximation). This  
954 approximation enabled us to produce stable 5-95% ranges with a Monte Carlo sample size of  
955  $2 \times 10^{10}$ . We also used kernel smoothing to produce satisfactorily smooth posterior PDFs. (We  
956 applied a Gaussian kernel smoother to the posterior PDFs with a standard deviation of 0.1 K, and  
957 found that this affected the 5-95% ranges by at most 0.02 K). Since in the Baseline calculation the  
958 feedback evidence yields a process PDF which is Gaussian in  $\lambda$  (cf. eqs. 13, 14), this can  
959 be reused as a feedback-based prior on total lambda and combined with the prior on  $\Delta F_{2xCO_2}$  via (  
960 15) and the downstream likelihoods via eqs. ( 14, 16), thus avoiding the need to sample from  
961 a prior on the  $\lambda_i$  feedbacks each time the calculation is repeated. This more streamlined calculation  
962 requires only a  $2 \times 10^8$  sample size and is used as the baseline for most of the sensitivity tests with  
963 a uniform- $\lambda$  prior in section 7. In calculations that use a uniform-S prior and omit process evidence  
964 (in sections 4 and 7), we speed up the calculations by sampling from uniform independent  
965 distributions for  $S$  and  $\Delta F_{2xCO_2}$ , calculating  $\lambda$  from eq. ( 4).

966

967

# 3. Constraints from Process Understanding

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## 3.1 Introductory concepts

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From equation ( 4), climate sensitivity is the amount of surface temperature increase necessary to induce a radiative response  $\Delta R$  whose energy loss to space cancels the energy trapped by a CO<sub>2</sub> doubling (the CO<sub>2</sub>'s *radiative forcing*  $\Delta F_{2\times CO_2}$ ). The radiative response  $\Delta R$  is achieved through changes in the various climate system constituents that influence Earth's radiation balance. The goals of "Process" research into climate sensitivity are to determine (a) the magnitude of CO<sub>2</sub> radiative forcing, and (b) the mix of changes in various climate system constituents that produces the necessary radiative response  $\Delta R$ . The responses of these constituents to warming are termed *feedback*. The constituents, including atmospheric temperature, water vapor, clouds, and surface ice and snow, are controlled by processes such as radiation, turbulence, condensation, and others. The CO<sub>2</sub> radiative forcing and climate feedback may also depend on chemical and biological processes.

984

### 3.1.1 Definitions of CO<sub>2</sub> radiative forcing and climate feedbacks

985

986

987

CO<sub>2</sub> radiative forcing  $\Delta F_{2\times CO_2}$ , with units  $W m^{-2}$ , includes both the direct radiative impact of doubling of atmospheric CO<sub>2</sub> and the indirect radiative impacts arising from adjustments of the atmosphere and surface that happen without the surface temperature  $T$  having appreciably risen.

988

989

990

For climate feedbacks, we expand upon eq. ( 5) to express the total climate feedback parameter  $\lambda$ , with units  $W m^{-2} K^{-1}$ , as the sum of the sensitivities of TOA radiation to factors  $x_i$  multiplied by how those factors  $x_i$  change with surface warming:

991

$$\lambda = \sum_i \lambda_i = \sum_i \frac{\partial N}{\partial x_i} \frac{dx_i}{\partial T} = \lambda_{Planck} + \lambda_{water\ vapor} + \lambda_{lapse\ rate} + \lambda_{surface} + \lambda_{clouds} + \lambda_{other} \quad (18)$$

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where  $x_i$  conventionally includes the changes in temperature (Planck), water vapor, lapse rate, surface albedo and clouds. Each of the terms on the right-hand side of eq. (18 ) is known as a "feedback", for example, the Planck feedback, water vapor feedback, lapse rate feedback, etc. Since  $\Delta F_{2\times CO_2}$  is defined per a prescribed atmospheric CO<sub>2</sub> concentration, carbon cycle feedback on CO<sub>2</sub> is excluded here. However, we also consider feedbacks  $\lambda_{other}$  from other changes in atmospheric composition such as those associated with atmospheric ozone and aerosol-cloud interactions and from changes in stratospheric temperature and water vapor not normally quantified. Readers interested in this conventional forcing-feedback theory may consult Hansen et al. (1984), Dessler and Zelinka (2015), Sherwood et al. (2015), and Hartmann (2016).

1001

### 3.1.2 Lines of evidence for process understanding

1002 Process evidence focuses on the current climate and its internal variability, excluding evidence  
1003 considered in the historical and paleoclimatic sections (section 4 and 5, respectively). There are  
1004 four primary sources for process evidence for  $S, \Delta F_{2\times CO_2}$  and climate feedbacks:

- 1005 • **Global Climate Models (GCMs).** Their strength is that they are a globally complete  
1006 representation of the climate system approximately satisfying known conservation laws of  
1007 energy, mass, and momentum. They can be used to estimate feedback and forcing from  
1008 idealized experiments, such as the simulation following an abrupt quadrupling of  $CO_2$  or an  
1009 atmosphere-model-only integration with quadrupled  $CO_2$  but fixed sea surface temperature  
1010 (SST) and sea-ice. One weakness is that they account for sub-grid processes, particularly  
1011 of clouds and convection, with approximate parameterizations whose varying  
1012 representations contribute to a large inter-model spread in the cloud feedback. Archives of  
1013 many GCM simulations, particularly those collected for the Coupled Model Inter-  
1014 comparison Projects (CMIP, Meehl et al., 2005; Taylor et al., 2012; Eyring et al., 2016),  
1015 have been used to determine the robust and non-robust aspects of GCM-simulated  $CO_2$   
1016 forcing and feedbacks.
- 1017
- 1018 • **Observations.** Short-term responses at global and regional scales can be quantified from  
1019 satellite observations of the covariation of TOA radiation with temperature, particularly from  
1020 inter-annual variability. These observable responses likely differ from those associated with  
1021  $CO_2$ -induced long-term warming, creating uncertainty as to the interpretation of short-term  
1022 feedback-like responses. GCMs can be used to test the correspondence between short-  
1023 term responses and the longer-term ones determining  $\lambda$  and  $S$ .
- 1024
- 1025 • **Process-resolving models.** High-resolution atmospheric simulations, such as “large-eddy  
1026 simulations” (LES), explicitly calculate the turbulence associated with clouds. These models  
1027 have increasingly been used to understand cloud feedbacks, primarily for tropical marine  
1028 low-level clouds, by forcing them with the environmental changes associated with climate  
1029 warming. Their simulated cloud responses are likely more realistic than those of GCMs  
1030 because LES resolves the main cloud-forming motions which GCMs must parameterize.  
1031 LES does however still contain parameterizations of cloud microphysics and the motions  
1032 that are smaller than the resolution of their grids, which is typically  $\sim 10$  m for boundary  
1033 layer clouds or  $\sim 100$  m for deep convection clouds. LES also cannot simulate all important  
1034 cloud conditions, must be forced by uncertain environmental changes from GCMs, and  
1035 for the case of boundary layer clouds, may be missing the effects of mesoscale motions  
1036 occurring at scales larger than their domain size. A very different type of process model  
1037 used to estimate the clear-sky direct component of  $\Delta F_{2\times CO_2}$ , is the observationally-verified  
1038 line-by-line radiative transfer model, which is more accurate than the radiative transfer  
1039 models used in GCMs.
- 1040
- 1041 • **Theory.** Although limited in precision, theory can provide critical assurance regarding  
1042 feedbacks inferred from the other sources. For example, basic thermodynamics supports  
1043 the lapse rate and water-vapor feedbacks. Also, the understanding that tropical  
1044 tropospheric overturning circulations are governed by the balance between subsidence  
1045 warming and clear-sky radiative cooling underlies the fixed-anvil temperature hypothesis  
1046 relating to the high-cloud altitude feedback.

1047 A new type of reasoning called *Emergent Constraints* arises by combining two of these primary  
1048 sources—GCMs and observations (Hall et al., 2019). Emergent constraints are empirical  
1049 relationships between a present-day climate system variable and a future climate change that  
1050 emerge in an ensemble of simulations by structurally-diverse GCMs. (More generally, emergent  
1051 constraints also exist using variables from other periods in the past but these are not discussed in  
1052 this section.) If the constraint is valid, one may infer a more likely estimate of the future change  
1053 when given an observation of the present-day variable. Using emergent constraints in this way can  
1054 be viewed as a kind of model weighting. Confidence in this inference depends on the strength of  
1055 the present-to-future relationship, the relative observational uncertainty of the present-day variable,  
1056 and how well the relationship is understood. Emergent constraints exist for  $S$  as well as individual  
1057 feedbacks, and are used to inform our assessment.

### 1058 **3.1.3 Methodology for assessing process understanding**

1059 As discussed in section 2.4, we use two approaches to assess the constraints on  $S$ . We do not  
1060 assess  $S$  directly, but rather assess  $\Delta F_{2xCO_2}$ ,  $\lambda$  and  $\lambda_i$ , which are related to  $S$  via eqs. (4) and (18  
1061 ).

1062 In the primary approach, we use all sources of evidence to determine a prior for  $\Delta F_{2xCO_2}$  (section  
1063 3.2.1) and likelihood functions for each individual feedback component  $\lambda_i$  in eq. (18). Consistent  
1064 with our target definition of  $S$ , we characterize the feedbacks  $\lambda_i$  acting over the 150 years following  
1065 an increase of  $CO_2$ . The relatively certain Planck, water vapor, lapse rate, surface albedo, and  
1066 other feedbacks are assessed in sections 3.2.2-3.2.5, and in section 3.3 we assess the cloud  
1067 feedback which is much more uncertain than the other feedbacks. For the cloud feedback we  
1068 assume that the total cloud feedback is a linear sum of feedbacks from individual cloud types, each  
1069 of which we consider separately. Such an approach is necessary to fully exploit our current  
1070 understanding, much of which pertains to specific cloud types. In section 3.4, we combine the  
1071 results from individual feedbacks to derive PDFs for the total cloud feedback and total climate  
1072 feedback parameter  $\lambda$ . Finally, in section 3.5 we examine observations of global inter-annual  
1073 radiation variability to address the concern that we might have missed some important feedbacks  
1074 through our method of combining individual feedbacks.

1075 In the secondary approach, we consider emergent constraints that have been used to directly infer  
1076  $S$  based upon the relationships between  $S$  and present-day climate system variables exhibited in  
1077 GCM ensembles. This evidence is given its own distinct likelihood function in section 3.6, where  
1078 we also discuss the relative independence of this evidence from that used in the primary approach  
1079 and why greater caution in the use of this evidence is required.

1080 A summary of all assessed process understanding of  $S$  then follows in section 3.7.

### 1081 **3.1.4 Further considerations**

1082 Both approaches are consistent with the effective climate sensitivity  $S$  definition used (section 2.1).  
1083 Thus, when considered, GCM feedback estimates are generally calculated from the linear  
1084 regression of associated anomalies on global mean surface air temperature during the first 150  
1085 years of the abrupt  $4xCO_2$  experiment simulations. One problem with this approach is that GCM  
1086 feedback estimates calculated in this manner when combined with a  $CO_2$  forcing that uses surface  
1087 albedo and tropospheric adjustments from fixed-SST GCM experiments (section 3.2.1) would  
1088 overestimate our target definition of  $S$  by ~15%. (This is because the  $CO_2$  forcing estimated from  
1089 fixed-SST experiments is ~15% larger than that estimated via ordinary linear regression from



1090 abrupt 4xCO<sub>2</sub> experiments.). However, because this error only affects feedback estimates from  
1091 GCMs and not the feedback estimates from theory, LES or observations of inter-annual variability,  
1092 the overall impact on the feedback values estimated with the primary approach would be much  
1093 less (< 5%) and is accordingly neglected.

1094 Mathematically, Gaussian likelihoods are assigned for each individual feedback component  $\lambda_i$ . This  
1095 means that we assume that the likelihood is a Gaussian function of the variable being assessed,  
1096 requiring that we specify two parameters—the mean and standard deviation. Note that if a  
1097 Gaussian likelihood function is applied to a variable with a broad (e.g., uniform) prior PDF in that  
1098 variable, the implied posterior PDF will also be Gaussian with the same mean and standard  
1099 deviation. Broad priors are appropriate for feedback components for which we do not have an a  
1100 priori expectation of their value, and which can be positive or negative (our Baseline prior case).  
1101 Hence, the likelihood functions for  $\lambda_i$  determined below can be considered equivalent to PDFs for  
1102 this case.  
1103

## 1104 **3.2 Process understanding of CO<sub>2</sub> radiative forcing and** 1105 **non-cloud feedbacks** 1106

### 1107 **3.2.1 CO<sub>2</sub> radiative forcing**

1108  
1109 Increases in CO<sub>2</sub> lead, all other things unchanged, to a decrease in longwave (LW) emission to  
1110 space (i.e., the CO<sub>2</sub> “greenhouse effect”). This instantaneous radiative forcing for a doubling of  
1111 CO<sub>2</sub> can be obtained from very accurate line-by-line radiative transfer models (Collins et al., 2006,  
1112 Pincus et al., 2015, Etminan et al., 2016); these are in very good agreement and provide a global-  
1113 mean estimate of 2.9 W m<sup>-2</sup> at the TOA (Figure 3 ). The instantaneous CO<sub>2</sub> radiative forcing  
1114 varies with location due to variations in temperature, water vapor, clouds, and tropopause position  
1115 (Huang et al., 2016a). The traditionally-defined forcing also includes a contribution from the  
1116 perturbed stratosphere because the stratosphere is dynamically isolated from the surface (Hansen  
1117 et al., 1981). Within a few months, the stratosphere cools in response to increased CO<sub>2</sub> causing an  
1118 additional reduction in the emission to space of LW radiation. This “stratospheric adjustment” is  
1119 well-understood and is estimated to add 0.9 W m<sup>-2</sup> at the TOA (Figure 3 ).  
1120

1121 Using an updated line-by-line radiative transfer model that also includes the shortwave absorption  
1122 bands of CO<sub>2</sub> as well as the spectral overlap with N<sub>2</sub>O absorption bands, Etminan et al. (2016)  
1123 estimate the sum of the instantaneous radiative forcing and the stratospheric adjustment, often  
1124 called the stratospheric-adjusted radiative forcing (SARF), to be 3.8 W m<sup>-2</sup> for a doubling of CO<sub>2</sub>,  
1125 using the equation in their Table 1. They also show that the radiative forcing increases slightly  
1126 more than logarithmically with CO<sub>2</sub> concentration. The 5-95% percentile uncertainty range for the  
1127 SARF is estimated to be ±10% (i.e., ±0.38 W m<sup>-2</sup>), with major components of the uncertainty due  
1128 to the radiative transfer code, the method of calculating the stratospheric adjustment, and the  
1129 specification of temperature, clouds, and tropopause position (Hodnebrog et al., 2013; Etminan et  
1130 al., 2016). Uncertainties due to spectroscopic data themselves are considered to be much smaller  
1131 (< 1%) (Mlynczak et al., 2016).  
1132

1133 Components of the surface and troposphere also adjust in response to the increase in CO<sub>2</sub>,  
1134 independent of the rise in surface temperature (Gregory and Webb 2008; Boucher et al., 2013).  
1135 They are fundamentally the same as the stratospheric adjustment in a sense that they occur  
1136 rapidly to modulate the TOA radiative flux (Sherwood et al., 2015), but their estimates are  
1137 methodologically distinct as currently these tropospheric and surface adjustments can be  
1138 estimated globally only from GCMs (Vial et al., 2013; Zhang and Huang, 2013; Smith et al., 2018).  
1139 Clouds are one component with reductions of low and middle-level clouds producing a positive  
1140 radiative adjustment of  $\sim 0.4 \text{ W m}^{-2}$  (Andrews et al., 2012b, Kamae et al., 2015, Sherwood et al.,  
1141 2015, Smith et al., 2018). Several mechanisms for these cloud reductions have been identified.  
1142 First, the increase in CO<sub>2</sub> causes the vertical profile of radiative cooling to shift to higher levels.  
1143 This results in less radiative cooling at low levels, a shoaling of the marine boundary layer, and a  
1144 reduction of low clouds (Kamae and Watanabe 2013). LES also simulates boundary layer shoaling  
1145 and low cloud reductions (Bretherton et al., 2013, Bretherton and Blossey, 2014, Blossey et al.,  
1146 2016), lending credence to the GCM results. Second, the increase in CO<sub>2</sub> also causes a reduction  
1147 in the vertically-integrated tropospheric radiative cooling, which reduces the strength of the overall  
1148 hydrologic cycle and hence the overall amount of cloud produced (Dinh and Fueglistaler, 2020).  
1149 Finally, plant physiological processes cause the stomatal resistance to increase with increasing  
1150 CO<sub>2</sub> (Doutriaux-Boucher et al., 2009). The resulting reduction in surface evaporation and  
1151 concomitant increase in sensible heat flux to the atmospheric boundary layer dries and warms the  
1152 near surface air. This reduces the low-level relative humidity and clouds over land (Arellano et al.,  
1153 2012, Andrews and Ringer, 2014).

1154  
1155 Other adjustments include negative ones from increased LW emission to space from a warmer  
1156 troposphere and increased land-surface temperatures, and positive ones from increased water  
1157 vapor and reduced surface albedo (Figure 3 ; Andrews et al., 2012b; Kamae and Watanabe  
1158 2012; Vial et al., 2013; Smith et al., 2018). The increase in land-surface temperature in these GCM  
1159 experiments results from the increase in surface downward LW radiation (itself the direct  
1160 consequence of the increased CO<sub>2</sub> concentration), and happens despite the simulations being  
1161 performed with fixed SSTs. The land surface warming slightly increases the global-mean surface  
1162 temperature, and its inclusion would be inconsistent with a definition of radiative forcing which  
1163 counts only those adjustments that occur without change in the global-mean surface temperature.  
1164 Thus, we exclude the land-surface warming component, yielding a total of  $+0.2 \text{ W m}^{-2}$  as the sum  
1165 of surface albedo and tropospheric adjustments, as calculated from the data in Smith et al. (2018).  
1166 (In reality, a portion of the other surface and tropospheric adjustments are the consequence of the  
1167 land-surface warming and also should be excluded. However, current research has not isolated  
1168 the portion of these adjustments that results from the land-surface warming from the portion that  
1169 directly responds to the CO<sub>2</sub> concentration.)

1170  
1171 The sum of the instantaneous radiative forcing and the stratospheric, tropospheric, and surface  
1172 albedo adjustments is known as the “effective” radiative forcing (ERF) and for a doubling of CO<sub>2</sub>  
1173 will be denoted with the symbol  $\Delta F_{2\times\text{CO}_2}$ . From the above arguments and Figure 3 , we estimate  
1174 the Gaussian prior of  $\Delta F_{2\times\text{CO}_2}$  to have a mean of  $2.9 + 0.9 + 0.2 = 4.0 \text{ W m}^{-2}$ . As for uncertainty in  
1175 the ERF, we assign its 5-95% percentile uncertainty range to  $\pm 0.5 \text{ W m}^{-2}$ , where the increase in  
1176 uncertainty above that of the SARF is attributed to the additional source of uncertainty from the  
1177 surface and tropospheric adjustments (dominated by the clouds) (Smith et al., 2018). Interpreting  
1178 this uncertainty as being Gaussian-distributed, we determine the standard deviation to be  $0.3 \text{ W m}^{-2}$ .  
1179 Altogether, we assess the prior of  $\Delta F_{2\times\text{CO}_2}$  to be  $N(+4.0, 0.3)$ , where we use the notation  $N(x,y)$  to  
1180 indicate a Gaussian distribution with mean  $x$  and standard deviation  $y$ .

1181

1182 To estimate the CO<sub>2</sub> ERF for perturbations other than a doubling, different approaches are used in  
1183 the paper. To estimate a CO<sub>2</sub> ERF time series over the historical period, section 4 uses the  
1184 equation for SARF in Table 1 of Etminan et al. (2016) scaled by the ratio of ERF to SARF for CO<sub>2</sub>  
1185 doubling which is 4.0/3.8 (an increase of 5%). The scaling factor is applied under the assumption  
1186 that the sum of tropospheric and surface albedo adjustments is linearly proportional to the SARF.  
1187 Section 5 follows the same approach and also adjusts the forcing of CH<sub>4</sub> and N<sub>2</sub>O by the same 5%  
1188 factor, based upon the assumption that the adjustments behave similarly for these other well-  
1189 mixed greenhouse gases (GHG).  
1190

### 1191 **3.2.2 Planck feedback**

1192  
1193 The Planck feedback represents the extra emission to space of LW radiation arising from a  
1194 vertically uniform warming of the surface and the atmosphere with no change in composition.  
1195 Physical expectation for this feedback is that  $\lambda_{Planck} \approx -4\varepsilon\sigma T^3 \approx -3.3 \text{ W m}^{-2} \text{ K}^{-1}$  for present-day  
1196 conditions, and the values shown in Figure 4 from GCMs of  $-3.2 \pm 0.04 \text{ W m}^{-2} \text{ K}^{-1}$  (1-sigma)  
1197 (Vial et al., 2013; Caldwell et al., 2016; Colman and Hanson, 2017) and those from observations of  
1198 inter-annual variability (Dessler, 2013) are both in general agreement with this physical  
1199 expectation. Uncertainties in modeled  $\lambda_{Planck}$  arise from differences in the spatial pattern of  
1200 surface warming, and the climatological distributions of clouds and water vapor that determine the  
1201 planetary emissivity ( $\varepsilon$ ). In particular, the latter impacts the radiative temperature kernel, which is  
1202 often held fixed in studies of inter model spread, thus leading to slight underestimates of structural  
1203 uncertainty in  $\lambda_{Planck}$  within individual studies. Accounting for these issues, we assign the  
1204 likelihood function for the Planck feedback to be  $N(-3.2, 0.1)$ .  
1205

### 1206 **3.2.3 Water vapor and lapse rate feedbacks**

1207  
1208 The water vapor feedback quantifies the change in outgoing LW and absorbed SW radiation at the  
1209 top of the atmosphere due to changes in atmospheric water vapor concentration associated with a  
1210 change in global mean surface temperature. It arises because water vapor absorbs both LW and  
1211 SW radiation and its concentration is expected to increase exponentially with temperature. The  
1212 equilibrium (saturation) concentration increases following fundamental thermodynamic theory of  
1213 the Clausius-Clapeyron relationship. Although concentrations are usually below saturation (relative  
1214 humidity less than 100%), this difference is well understood (Sherwood et al., 2010a) and well  
1215 captured by GCMs with adequate resolution (Sherwood et al., 2010b). Increases in specific  
1216 humidity in response to 1 K of warming at constant relative humidity in the middle and upper  
1217 troposphere result in a greater reduction in outgoing LW radiation than similar increases in the  
1218 lower troposphere due to the masking effects of overlying water vapor and clouds (Soden et al.,  
1219 2008; Vial et al., 2013). A given increase in specific humidity generally has a larger impact on LW  
1220 than on SW radiation. GCM simulations and observations of the seasonal cycle, inter-annual  
1221 variability, and climate trends all exhibit relatively small changes in relative humidity with warming,  
1222 and therefore large increases in specific humidity with warming (Dessler and Sherwood, 2009;  
1223 Boucher et al., 2013). The agreement of observations and GCMs with expectations from basic  
1224 thermodynamic theory (Romps, 2014) leads to high confidence in robustly positive water vapor  
1225 feedback.  
1226

1227 The lapse-rate feedback is the change in LW radiation emitted to space resulting from any non-  
1228 uniformity of the change in temperature in the vertical. The LW emission to space depends on both  
1229 surface and atmospheric temperatures. The more the atmosphere warms per degree of surface  
1230 warming, the greater the increase in LW emission to space, and hence the greater the LW  
1231 radiative damping of surface warming. Low-latitude warming occurs along a moist adiabat such  
1232 that free-tropospheric warming exceeds that at the surface, causing a negative lapse-rate  
1233 feedback. At higher latitudes with greater stability and reduced coupling between the surface and  
1234 free troposphere, warming is generally largest near the surface, leading to a positive lapse rate  
1235 feedback (Manabe and Wetherald, 1975). Though consistently negative in the global mean, the  
1236 strength of the lapse rate feedback varies among models and between observational estimates.  
1237

1238 The impact of the separate uncertainties in these feedbacks on the climate feedback parameter  $\lambda$   
1239 is limited, however, because GCMs and physical reasoning suggest that these two feedbacks are  
1240 strongly anti-correlated (Zhang et al., 1994; Soden and Held, 2006; Held and Shell, 2012). This is  
1241 fundamentally because radiation to space depends to good approximation on the relative humidity,  
1242 which changes little overall with warming as mentioned above, and the near-surface temperature  
1243 (Ingram, 2010). Although the anti-correlated spread of the two feedbacks in models was thought  
1244 to arise because models experiencing greater upper tropospheric warming also experience greater  
1245 moistening of the upper troposphere, it is now clear that the varying partitioning of surface warming  
1246 between the tropics and extratropics is responsible. Specifically, models with warming  
1247 concentrated at low latitudes have larger negative extratropical lapse rate feedbacks and stronger  
1248 positive extratropical water vapor feedbacks (Po Chedley et al., 2018). As a result of this anti-  
1249 correlation, it is useful to consider the sum of the lapse-rate plus water vapor feedback, which is  
1250 much less uncertain than the individual components. Still there remains structural or  
1251 methodological uncertainty with studies coming up with ensemble mean estimates of  $0.9\text{--}1.4 \text{ W m}^{-2} \text{ K}^{-1}$   
1252 (Figure 4 ), which exceeds the inter-model spread. This could partly be due to the use of  
1253 different radiative kernels, and likely related to shortwave absorption by water vapor (Pincus et al.,  
1254 2015). These central estimates are in quantitative agreement, though, with estimates based on  
1255 reanalysis (Dessler, 2013) (Figure 4 ). From this agreement and with consideration of the  
1256 uncertainty in both reanalysis and GCM estimates, we therefore assess the likelihood function for  
1257 the lapse-rate plus water-vapor feedback to be  $N(+1.15, 0.15)$ .  
1258

### 1259 **3.2.4 Surface albedo feedback**

1260  
1261 The surface albedo feedback mostly arises from warming-induced shrinkage of the cryosphere,  
1262 which exposes less reflective surfaces that absorb more sunlight. It is dominated by snow and sea  
1263 ice at high latitudes. Its strength is determined primarily by how snow and ice vary with global  
1264 mean temperature; the contrast in albedo between frozen and non-frozen surfaces; and the  
1265 shortwave transmissivity of the atmosphere as the photons have to traverse the atmosphere at  
1266 least twice to be reflected to space by the surface. Quantitative estimates from GCMs and  
1267 observations based on inter-annual variability generally agree, with a feedback value near  $0.3$   
1268  $\text{W m}^{-2} \text{ K}^{-1}$  (Figure 4 ), and GCMs suggest that the feedback value implied by inter-annual  
1269 variability is near that in response to long-term  $\text{CO}_2$  warming (section 3.5 ). The relevance of  
1270 internal climate variability to global warming is also supported by an emergent constraint from the  
1271 seasonal cycle for the surface albedo feedback which is very strong on Northern Hemisphere land  
1272 and is mostly caused by snow cover changes (Hall and Qu, 2006; Qu et al., 2007, 2014). Early  
1273 attempts to form an emergent constraint on sea ice feedbacks were less encouraging (Crook and

1274 Forster, 2014; Colman, 2013), however recent progress has been achieved by taking advantage of  
1275 the seasonal cycle in Arctic sea ice to constrain its contribution to global feedback (Thackeray and  
1276 Hall, 2019). Mostly, this progress arises from a focus on surface albedo feedback in near-term  
1277 global warming, well before Arctic sea ice vanishes.

1278

1279 However, uncertainties can be larger than apparent in these comparisons for various reasons.  
1280 Observed trends in surface albedo for the period 1979 to 2008, driven mostly by Northern  
1281 Hemisphere sea ice loss, suggest a larger value of surface albedo feedback (Flanner et al., 2011;  
1282 Pistone et al., 2014; Cao et al., 2015), although internal decadal variability may also be  
1283 contributing to the diagnosed feedback in this period. Atmospheric transmissivity largely depends  
1284 on liquid or mixed phase clouds in the Arctic summer season, and since many GCMs fail to  
1285 simulate these clouds (Karlsson and Svensson, 2013; Pithan et al., 2014), GCMs likely  
1286 overestimate the surface albedo feedback. The surface albedo feedback is also state dependent  
1287 such that reduced cryospheric extent will reduce its magnitude in a warmer climate (Jonko et  
1288 al., 2012; Block and Mauritsen, 2013, Thackeray and Hall, 2019). Separately, some GCMs  
1289 exaggerate snow albedo feedback on land because they do not account for vegetation masking  
1290 (Qu and Hall, 2007, 2014; Thackeray et al., 2018).

1291

1292 Based upon the good agreement between the observed estimate from inter-annual variability and  
1293 the GCM values for both inter-annual variability and long-term warming, we assign a central  
1294 estimate of surface albedo feedback as  $0.3 \text{ W m}^{-2} \text{ K}^{-1}$ . As the just-discussed uncertainties do not  
1295 have a consistent sign, we do not alter the central estimate, but double the quantitative  
1296 uncertainties diagnosed from observations (Dessler, 2013) and GCM inter-model spread. Thus, we  
1297 assess the likelihood function for the surface albedo feedback to be  $N(+0.3, 0.15)$ .

1298

1299 Apart from the cryosphere, a small positive surface albedo feedback comes from the inundation of  
1300 coastal lands by sea level rise which thus replaces land with a less reflective ocean surface. For  
1301 the Last Glacial Maximum (LGM), the estimated radiative effect is of order  $1 \text{ W m}^{-2}$  (Köhler et al.,  
1302 2010, see section 5.1). But because sea-level rise realized during 150 years and several K of  
1303 warming would be limited to at most a few meters compared to the LGM change of over 100  
1304 meters, the resulting effective feedback is only of order  $0.01 \text{ W m}^{-2} \text{ K}^{-1}$ . Other surface albedo  
1305 feedbacks can occur as a function of changing precipitation patterns affecting soil moisture,  
1306 vegetation changes in response to moisture and/or temperature changes, and changes in surface  
1307 chlorophyll in response to ocean circulation changes. Calculations suggest that these feedbacks  
1308 are also negligible on global mean temperature, although they can significantly affect regional  
1309 climate changes (Levis et al., 1999).

1310

1311

### 1312 **3.2.5 Stratospheric feedback**

1313

1314 The feedback estimates shown in Figure 4 do not include those from the response of  
1315 stratospheric temperature and water vapor to climate warming. Banarjee et al. (2019) calculate a  
1316 stratospheric water vapor feedback of  $+0.15 \pm 0.04 \text{ W m}^{-2} \text{ K}^{-1}$  (1-sigma) from 27 CMIP5 model  
1317 simulations of the abrupt 4xCO<sub>2</sub> experiment, resulting from the robust increase in stratospheric  
1318 water vapor in each model. Climate warming however increases the strength of the Brewer-  
1319 Dobson circulation; this forces temperature anomalies that compensate for those induced by water  
1320 vapor, with the result that the net feedback is smaller. From 11 CMIP5 models, Huang et al.  
1321 (2016b) quantify the total feedback from changes in stratospheric temperature and water vapor to  
1322 be  $0.00 \pm 0.04 \text{ W m}^{-2} \text{ K}^{-1}$  (1-sigma).

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Based upon this study, we assess the likelihood function for this total stratospheric physical feedback to be  $N(+0.0, 0.10)$ , where the increased standard deviation is justified by a lack of confidence in the fidelity with which the CMIP5 GCMs used by Huang et al. (2016b) simulate stratospheric processes. Increased standard deviation is also justified by the lack of quantitative confirmation from observations. However, qualitative observational support for our assessment exists. Specifically, observations show that increases in lower stratospheric water vapor in inter-annual variability are correlated to increases in tropospheric temperature (Dessler et al., 2013) and observations support the notion that the Brewer-Dobson circulation has strengthened over the most recent four decades (Fu et al., 2015; Fu et al., 2019).

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### 3.2.6 Feedbacks from other atmospheric composition changes

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In this assessment we consider well-mixed gases ( $\text{CO}_2$ ,  $\text{CH}_4$ ,  $\text{N}_2\text{O}$ ) to be specified forcings, since in the modern era, they are effectively under human control. Thus we do not include climate-driven variations of these gases (e.g., carbon cycle feedbacks). However, this still leaves several possible sources of feedback apart from the traditional ones discussed so far.

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One example is ozone, an absorber of both SW and LW radiation whose chemistry responds to temperature and temperature-mediated circulation changes. The direct feedback from climate-driven tropospheric ozone changes appears negligible (Dietmuller et al., 2014). However, the indirect effects of ozone changes could be considerable with one study suggesting that interactive ozone chemistry induces a substantial negative feedback averaging  $0.13 \text{ W m}^{-2} \text{ K}^{-1}$  (Nowack et al., 2015). In their study, the robust strengthening of the Brewer-Dobson circulation in a warmer climate causes a reduction of tropical lower-stratospheric ozone, and because this region is particularly cold this leads to a reduction of the greenhouse effect. Follow-up studies with other models found similar ozone concentration changes, but similar or smaller impacts on the climate feedback parameter  $\lambda$  in response to  $\text{CO}_2$ -induced climate change (Marsh et al., 2016; Chiodi and Polvani, 2017; Dacie et al., 2019). In contrast, a larger impact has been identified in response to solar forcing (Chiodi and Polvani, 2016), and with stronger impacts on atmosphere and ocean circulations (Muthers et al., 2016; Chiodi and Polvani, 2017; Nowack et al., 2017). Simulations with fully interactive atmospheric chemistry in the GISS CMIP5 models had a  $\sim 10\%$  increased  $S$  compared to non-interactive versions (Schmidt et al., 2014), and this change was influenced in part by the ozone changes, but also the direct and indirect aerosol responses to a higher  $\text{CO}_2$  world.

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A warmer climate could also affect the production and/or lifetime of aerosols, in particular, dust, sea salt, natural sources of  $\text{SO}_2/\text{SO}_4$  and reactive nitrogen species, and natural fires. Besides changes to the direct aerosol radiative effect (Paulot et al., 2020), this could lead to additional indirect aerosol effects on clouds (Gettelman and Sherwood, 2016; Gettelman et al., 2016) and fire-induced effects on surface albedo. For example, one recent study showed that the increase in Southern Ocean emissions of primary organic matter and gaseous dimethyl sulfide with climate warming could impact the climate feedback parameter  $\lambda$  by  $0.2 \text{ W m}^{-2} \text{ K}^{-1}$  depending on how the aerosol change affected cloud droplet number (Bodas-Salcedo et al., 2019). Another recent study showed that the increase with warming of sea-salt emissions altered  $\lambda$  by  $0.13 \text{ W m}^{-2} \text{ K}^{-1}$  (Paulot et al., 2020). A review of possible mechanisms (Carslaw et al., 2010) suggested high uncertainty but a possible total effect of up to  $\pm 0.2 \text{ W m}^{-2} \text{ K}^{-1}$  over the 21st century. A direct  $\text{CO}_2$  effect to the

1369 biophysical change in stomatal conductance over land has been accounted for in many GCMs,  
1370 and has been discussed in section 3.2.1.

1371

1372 In the absence of evidence for a systematic effect, we assess these processes have no expected  
1373 net effect and assign the mean of the likelihood function for  $\lambda_{other}$  to zero. For the standard  
1374 deviation, we base our quantitative estimate on the Nowack et al. (2015), Schmidt et al. (2014),  
1375 and Carslaw et al. (2010) studies, and assign a value of  $0.15 \text{ W m}^{-2} \text{ K}^{-1}$ .

1376

### 1377 **3.3 Process understanding of cloud feedbacks**

1378

1379 Because both observations and GCMs indicate that the largest uncertainty resides with the cloud  
1380 feedback (Figure 4 ), it has been the main focus of climate feedback research for the past three  
1381 decades. The cloud feedback is particularly difficult since there are diverse cloud formation  
1382 processes, most of which are challenging to represent in GCMs, and we must add up the response  
1383 to warming of all cloud types capable of making a significant radiative contribution.

1384

1385 Given this complexity, it is logical to start by considering the mean and range of GCM simulations  
1386 of both present-day zonal mean cloud fraction and its response to global warming (Figures 5 a-  
1387 b), and the corresponding radiative impact (Figures 5 c-e), noting the simulated roles of various  
1388 cloud types. (Note that these GCM cloud feedbacks are presented only to orient the reader for the  
1389 following sections, which will assess specific cloud feedbacks based upon all of the evidence from  
1390 observations, process-resolving models, theory, and GCMs.)

1391

1392 Even though GCMs disagree significantly on the value of the total cloud feedback, at least 80% of  
1393 25 CMIP5 models agree on the direction of change in cloud cover over 80% of the atmosphere  
1394 (see stippling in Figure 5 a). This indicates that GCMs broadly agree on many large-scale  
1395 responses including an upward shift of clouds near the tropopause, a poleward shift of clouds in  
1396 midlatitudes, and a decrease in clouds of  $0.5\text{-}1\% \text{ K}^{-1}$  in most of the troposphere. The inter-model  
1397 standard deviation of cloud fraction response to warming (Figure 5 b) can be considered an  
1398 internal measure of model uncertainty. It tends to be greatest in regions where the multi-model  
1399 mean cloud fraction is large, more so for tropical boundary layer and deep convective clouds.

1400

1401 Figure 5 c shows the corresponding zonally-averaged cloud feedbacks, with a solid line shown  
1402 at latitudes where at least 14 of the 18 GCMs providing the needed data agree on the feedback  
1403 sign. Equatorward of  $50^\circ$  latitude, GCMs robustly predict positive feedback, of which more than  
1404 half is due to low cloud. Most of the positive non-low (i.e., high and middle level) cloud feedback is  
1405 due to cloud altitude shifts (Figure 5 d), whereas most of the positive low cloud feedback is due  
1406 to cloud fraction reductions (Figure 5 e). Negative cloud feedbacks near  $60^\circ\text{S}$  are primarily due  
1407 to an increase in cloud optical depth (opacity), particularly in low cloud.

1408

1409 Our level of understanding of the physical processes responsible for these patterns of cloud  
1410 response and radiative feedback varies. We begin with cloud feedbacks that are considered more  
1411 certain (high cloud altitude) or important (tropical low cloud) before discussing less certain  
1412 feedbacks associated with other cloud types.

1413

### 1414 3.3.1 High-cloud altitude feedback

1415

1416 The altitude of high-cloud tops is expected to increase with global warming, a response that arises  
1417 from relatively basic physics. Convective mixing in the tropics occurs only at altitude ranges  
1418 experiencing substantial radiative cooling by water vapor (Manabe and Strickler, 1964), which  
1419 expand upward as the atmosphere warms if relative humidity does not change substantially.  
1420 Because anvil clouds form from detrainment near the top of the convecting layer, they too are  
1421 expected to rise with warming, roughly isothermally (Hartmann and Larson, 2002). Because cloud-  
1422 top temperature and hence longwave emission to space from high cloud tops does not increase in  
1423 step with the warming atmosphere and surface below, this response impedes the planet's ability to  
1424 radiate away extra energy—a positive radiative feedback (Yoshimori et al., 2020). This notion can  
1425 be traced back at least as far as Cess (1974), who showed that the empirical relationship between  
1426 temperature and outgoing LW flux (Budyko, 1969) was better explained by cloud top temperature  
1427 rather than altitude staying constant with surface warming.

1428

1429 Observations of inter-annual variability confirm that tropical high clouds rise with surface warming  
1430 (Eitzen et al., 2009; Li et al., 2012; Xu et al., 2005, 2007; Zelinka and Hartmann, 2011; Zhou et al.,  
1431 2014, Vaillant de Guélis et al., 2018). Using interannual variability in cloud properties observed by  
1432 CALIPSO over 2008–2014, Vaillant de Guélis et al. (2018) estimate a global mean short-term LW  
1433 cloud altitude feedback of  $0.86 \pm 0.48 \text{ W m}^{-2} \text{ K}^{-1}$  (1-sigma). Scaling this short-term value by the  
1434 ratio of short- to long-term altitude feedbacks in a single GCM computed using the same  
1435 methodology implies a long-term value of  $0.35 \pm 0.20 \text{ W m}^{-2} \text{ K}^{-1}$ . Further observational analyses for  
1436 longer periods and examination of the relationship between short- and long-term altitude  
1437 feedbacks in more GCMs are needed. At longer time-scales, the climate-change induced upward  
1438 shift of high clouds is expected to be detectable and distinct from the noise of internal variability  
1439 sooner than for other cloud properties (Chepfer et al., 2014; Marvel et al., 2015). Indeed, 25-year  
1440 trends from artifact-corrected ISCCP and PATMOS-x satellite datasets (Norris and Evan, 2015)  
1441 indicate an upward shift of high clouds, suggesting that this signal may already be emerging from  
1442 the noise (Norris et al., 2016).

1443

1444 An increasing altitude of high clouds with warming has been simulated ever since GCMs began  
1445 predicting cloud distributions (Hansen et al., 1984; Wetherald and Manabe, 1988), and is clearly  
1446 seen in Figure 5 a. All current climate models simulate a positive feedback from increases in the  
1447 altitude of high cloud tops with global warming (Zelinka and Hartmann, 2010; Zelinka et al., 2012b;  
1448 Zelinka et al., 2013). This feedback has a mean and one standard deviation of 0.20 and  $0.10 \text{ W m}^{-2} \text{ K}^{-1}$   
1449 across all GCMs (including some CMIP6 models) that have provided the necessary  
1450 diagnostics to perform the calculations in Zelinka et al. (2016). The purple curve in Figure 5 d  
1451 shows the multi-model mean latitudinal dependence of this longwave cloud radiative feedback.  
1452 The simulated increase in altitude is a global phenomenon, but its strength is modulated regionally  
1453 by the mean-state high cloud distribution. In model simulations, a slight warming of cloud tops  
1454 occurs rather than the purely isothermal response anticipated by Hartmann and Larson (2002).  
1455 This has been attributed to increases in upper tropospheric stability (Zelinka and Hartmann, 2010;  
1456 Bony et al., 2016), but can be modulated by changes in humidity (Kluft et al., 2019), ozone and  
1457 stratospheric upwelling (Dacie et al., 2019), and additional processes (Seeley et al., 2019b). The  
1458 same principles have been shown to apply in the extratropics, providing support for the positive  
1459 extratropical cloud altitude feedback (Thompson et al., 2017) which GCMs suggest is comparable  
1460 in magnitude to the tropical cloud altitude feedback. Depletion of condensate by mixing with the  
1461 drier environment is also relevant for high cloud coverage and its vertical shifts with warming



1462 (Seeley et al., 2019a) but should not affect the basic result that warming increases high cloud  
1463 altitude.

1464  
1465 Tropical clouds also shift upward nearly isothermally with warming in cloud resolving models and  
1466 large eddy simulations (Harrop and Hartmann, 2012; Khairoutdinov and Emanuel, 2013; Kuang  
1467 and Hartmann, 2007; Narenpitak et al., 2017; Tompkins and Craig, 1999). Global cloud resolving  
1468 model simulations further support this upward shift, including in the extratropics (Bretherton et al.,  
1469 2014; Satoh et al., 2012; Tsushima et al., 2014). The cloud altitude feedback diagnosed in  
1470 Bretherton et al. (2014) falls within the range of conventional GCMs quoted above, providing an  
1471 important confirmation of its sign and magnitude in a model that explicitly simulates cumulus  
1472 convection.

1473  
1474 In summary, theoretical, observational, high-resolution modeling and GCM studies all support a  
1475 positive high-cloud altitude feedback. Given that GCMs appear to represent the relevant physics  
1476 and have a mean feedback within the uncertainty estimate of a limited first observational estimate,  
1477 we assess the likelihood function of the high-cloud altitude feedback to be  $N(+0.20, 0.10)$ , where  
1478 the mean and standard deviation corresponds to that of GCMs. This assumes that GCMs well  
1479 sample the uncertainty in the effective high-cloud amount and the rate at which the high-cloud  
1480 altitude will rise with warming.

1481

### 1482 **3.3.2 Tropical marine low-cloud feedback**

1483

1484 Uncertainties in the response to climate change of low-latitude marine boundary-layer clouds  
1485 (cumulus and stratocumulus) in subsiding regions remain a central challenge. The GCM inter-  
1486 model spread in the tropical low cloud feedback is large and well correlated with inter-model  
1487 spread in  $S$  (Bony and Dufresne, 2005; Vial et al., 2013). However, a combination of process-  
1488 resolving modeling and new observational analysis is leading to a better understanding and  
1489 quantification of the most important cloud response mechanisms, leading to increasing confidence  
1490 that this regime contributes to positive global cloud feedback.

1491

1492 The feedback of low clouds is almost exclusively via shortwave radiation because they have a  
1493 small effect on TOA longwave radiation. Figure 5 e shows that most GCMs simulate positive low  
1494 cloud feedbacks throughout low latitudes (30°S-30°N) which are especially strong in the deep  
1495 tropics (10°S-10°N) and are almost exclusively due to reduced cloud amount in a warmer climate.  
1496 As will be discussed in section 3.3.5, GCMs also simulate positive low cloud feedback in  
1497 midlatitudes (30-50° latitude), where the mechanisms controlling low cloud are likely similar but  
1498 quantitatively less well constrained. Despite the general agreement among GCMs in the sign of the  
1499 feedback, the large inter-model spread has motivated major efforts to use other lines of evidence,  
1500 namely process-resolving models and observations, to infer the tropical low cloud feedback.

1501

1502 Bretherton et al. (2015) reviews results from large-eddy simulation (LES) of low-latitude marine  
1503 cloud-topped boundary layers in present-day versus perturbed climates. This work suggests that  
1504 four main mechanisms affect the cloud response on climate timescales. These are: (1) cloud  
1505 reduction due to thermodynamic effects of overall warming of the atmosphere-ocean column,  
1506 including the associated increase in specific humidity, (2) stratocumulus cloud reduction due to the  
1507 direct effect of CO<sub>2</sub> increases on boundary-layer radiative cooling, an important process for stirring  
1508 up cloud-forming turbulence (note this contributes to rapid adjustment to CO<sub>2</sub> (section 3.2.1), and

1509 not the temperature-mediated feedback that we are trying to determine here), (3) increases in the  
1510 stratification between the boundary layer and overlying free troposphere, favoring more cloud, and  
1511 (4) reductions in the mean subsidence rate, which favor more cloud by keeping the cloud layer  
1512 from shoaling. Other possible forcings, such as changes in free-tropospheric relative humidity and  
1513 surface wind speed, may be important for regional cloud response to climate change but seem to  
1514 be secondary to global cloud feedback. LES for the expected global warming environment typically  
1515 predict less low cloud, hence positive cloud feedback. This happens because the warming-induced  
1516 reduction in low cloud (mechanism (1)) overwhelms the increases from the small changes in  
1517 expected stratification and subsidence (mechanisms (3) and (4)).  
1518

1519 The cloudy boundary layer responds within hours to days to changes in the overlying atmosphere  
1520 or underlying ocean. Klein et al. (2017) reviews a series of observational analyses that have tried  
1521 to quantify the sensitivity of clouds to each of the 'cloud controlling factors' associated with the  
1522 mechanisms above using satellite observations of natural space-time variability on weekly to inter-  
1523 annual time scales (Qu et al., 2015; Zhai et al., 2015; Myers and Norris, 2016; Brient and  
1524 Schneider, 2016; McCoy et al., 2017). These studies also establish that in GCMs sensitivities to  
1525 these factors are similar for the century time-scale climate warming as for present-day climate  
1526 variability. Using the GCM predictions of how the controlling factors change with climate warming,  
1527 Klein et al. (2017) find positive thermodynamic feedback and a smaller, partially compensating  
1528 contribution from negative stability feedback; the effects of other possible cloud-controlling factors  
1529 are either small or difficult to observationally separate from these. They estimate a 90% confidence  
1530 interval for the local radiative feedback of low-latitude marine low clouds of  $0.3\text{-}1.7 \text{ W m}^{-2} \text{ K}^{-1}$   
1531 (Figure 6 ). They also compare their observational results to the LES studies reviewed by  
1532 Bretherton et al. (2015), finding that LES estimate a similar range of positive cloud feedback, with  
1533 trade cumulus regimes in the lower half of this range and stratocumulus regimes in the upper half  
1534 of this range. Observations from Cesana et al. (2019) also support the notion that the positive  
1535 feedback from trade cumulus regimes will be smaller than those from stratocumulus regimes.  
1536

1537 Given the agreement between observations and LES shown in Figure 6 , we base our assessed  
1538 tropical low cloud feedback on these two lines of evidence. Since 25% of the globe is covered by  
1539 marine tropical subsidence regimes, the local feedbacks shown in Figure 6 are multiplied by  
1540 0.25 leading to the Klein et al. (2017) estimate that the tropical low-cloud contribution to the global  
1541 cloud feedback is  $0.25 \pm 0.11 \text{ W m}^{-2} \text{ K}^{-1}$  (1-sigma). Thus we assign the mean value of the  
1542 likelihood function of the tropical low cloud feedback to  $+0.25 \text{ W m}^{-2} \text{ K}^{-1}$ . However, we have  
1543 subjectively chosen to increase the standard deviation of likelihood function from  $0.11 \text{ W m}^{-2} \text{ K}^{-1}$  to  
1544  $0.16 \text{ W m}^{-2} \text{ K}^{-1}$ , reflecting methodological uncertainties in the direct use of LES and current climate  
1545 observations to infer climate change.  
1546

1547 It is important to recognize that these estimates rely on the environmental conditions applied to  
1548 LES and the observations. These boundary conditions were taken from GCM climate change  
1549 simulations dominated by  $\text{CO}_2$  warming. If future changes in boundary conditions differ from those  
1550 predicted, this would imply a different response of low clouds. In particular, over the historical  
1551 period from 1980-2015, the tropical western Pacific SST increased markedly with little or no  
1552 change of tropical eastern Pacific SST. This pattern of SST change caused an increase in the  
1553 strength of the capping inversion in tropical subsidence regions (Zhou et al., 2016). The net result  
1554 was increased low cloud in tropical subsidence regions, which can be understood to result from the  
1555 combination of very little warming-induced reduction of low cloud (mechanism (1)) and strong  
1556 stratification-induced increase in low cloud (mechanism (3)) (Seethala et al., 2015; Zhou et al.,  
1557 2016). Thus, due to the dependence of low cloud on the pattern of SST change, tropical low clouds

1558 increased even as the planet as a whole warmed over the period 1980-2015. This is the physical  
1559 explanation underlying the low-cloud contribution to the “pattern effect,” which significantly affects  
1560 interpretation of the historical record and is discussed in section 4.2.  
1561

### 1562 **3.3.3 Tropical anvil cloud area feedback**

1563  
1564 In addition to the positive feedback from high-level clouds rising in a warmer climate (section  
1565 3.3.1), a change in the areal coverage of these clouds in a warmer climate may exert a feedback.  
1566 Of particular interest is the response of “anvil” high clouds found in tropical deep convection  
1567 regions in conditions of high SST and large-scale ascent. These clouds are highly reflective of  
1568 solar radiation and at the same time greatly reduce the outgoing LW radiation to space (Kiehl  
1569 1994). Small changes in the balance between these large cooling and warming effects may cause  
1570 a significant radiative feedback on climate warming.  
1571

1572 A reduction in the area coverage of tropical anvil clouds with warming was first suggested to be a  
1573 strongly negative feedback by Lindzen et al. (2001), and is sometimes referred to as the “iris”  
1574 effect. Lindzen et al. (2001) hypothesized that the microphysical processes in convective updrafts  
1575 that provide much of the condensate for high-level clouds become more efficient with climate  
1576 warming causing a decrease in anvil cloud area. While GCMs show that the simulation of tropical  
1577 high clouds and their climate response are highly sensitivity to convective updraft microphysics  
1578 (Clement and Soden, 2005; Zhao, 2014; Mauritsen and Stevens, 2015; Zhao et al., 2016), there is  
1579 no clear evidence that precipitation efficiency would increase in a warmer climate.  
1580

1581 Another mechanism that could cause a decrease in anvil cloud area would be a tendency in a  
1582 warmer world towards increased convective organization—the propensity for clouds to cluster or  
1583 aggregate (Khairoutdinov and Emanuel, 2010; Mauritsen and Stevens, 2015). In both observations  
1584 (Tobin et al., 2012; Stein et al., 2017) and convection resolving models (Bretherton et al., 2005),  
1585 aggregated convective cases are considerably drier and have less upper-level clouds. However,  
1586 there is no clear evidence from cloud-resolving models that aggregation systematically increases  
1587 with temperature (Wing, 2019). Even if aggregation does not systematically vary with temperature,  
1588 the degree of aggregation in the base climate may affect climate feedbacks. This is because the  
1589 dryness and less upper-level cloud of aggregated states may cause smaller water vapor and high-  
1590 cloud altitude feedbacks (Wing, 2019), or increase the sensitivity to feedbacks from exposed low  
1591 clouds (Bony et al., 2016).  
1592

1593 Bony et al. (2016) proposed another mechanism for a decrease in anvil cloud area with warming  
1594 called a “stability iris.” Specifically, in a warmer world there is increased static stability at the levels  
1595 where convective updrafts detrain and form high-level clouds. This increased stability is associated  
1596 with a weaker radiatively-driven divergence at these heights, which results in less detrained mass  
1597 and hence less anvil cloud.  
1598

1599 While these proposed mechanisms generally suggest reduced anvil cloud area with warming, they  
1600 do not determine the net cloud radiative effect that would impact  $S$ . A separate theoretical  
1601 argument by Hartmann et al. (2001) posits that large-scale circulations act to keep net cloud  
1602 radiative effects of tropical deep convection regions close to the small net cloud radiative effects of  
1603 nearby non-convective regions. If such considerations apply to a warmer world, this would predict  
1604 small net cloud feedbacks from clouds in tropical deep convective regions.

1605

1606 As for GCMs, they are not deemed trustworthy for the simulation of anvil cloud area because they  
1607 lack sufficient cloud microphysics and convective organization processes, among other reasons.  
1608 GCMs also largely fail to reproduce the observed increase in outgoing LW radiation that  
1609 accompanies warming on interannual timescales (Mauritsen and Stevens, 2015) despite  
1610 simulating some decrease in anvil cloud area with warming at least in some models (Bony et al.,  
1611 2016). Thus little confidence is placed in the small GCM response of tropical high cloud area with  
1612 warming (Figure 5 d).

1613

1614 One might place greater confidence in convection-resolving models, but results are varied. While  
1615 cloud-resolving models run in limited-area or tropical channel domains tend to simulate decreases  
1616 in high cloud area with warming (Bony et al., 2016; Cronin and Wing, 2017), global or near-global  
1617 models with convection permitting resolution simulate little change (Bretherton et al., 2014,  
1618 Narenpitak et al., 2017) or even increases (Tsushima et al., 2014; Chen et al., 2016). The one  
1619 simulation with increased high cloud was very sensitive to the representation of ice cloud  
1620 microphysics and sub-grid-scale turbulence, suggesting that the current generation of convection-  
1621 resolving models may not provide definitive answers about the response of tropical high clouds to  
1622 warming (Bretherton et al., 2015).

1623

1624 This leaves observed variability as the primary guide to tropical high-cloud feedbacks, particularly  
1625 for the net radiative impact of high-cloud changes. Observational analyses focus on the response  
1626 of tropical high clouds to inter-annual variability, under the idea that short-term feedbacks in  
1627 tropical high clouds are relevant to their long-term climate feedbacks, an idea partially supported  
1628 by GCM analyses (Mauritsen and Stevens, 2015). Using CERES radiation budget measurements,  
1629 Williams and Pierrehumbert (2017) found that under warming, the large reduction in shortwave  
1630 reflection by fewer tropical deep convective clouds was a little bit smaller than the large reduction  
1631 in the longwave trapping by tropical deep convective clouds. The net result, seen in their Figure 3,  
1632 is a local cooling of  $1\text{-}5 \text{ W m}^{-2} \text{ K}^{-1}$ . We convert their estimate of a tropical feedback to a global  
1633 feedback by accounting for differences in area fraction and local versus global temperature  
1634 changes, and by removing an estimate of the positive cloud feedback from increased cloud altitude  
1635 (this is done so as not to double count the altitude feedback estimated in section 3.3.1). This yields  
1636 an estimate of the tropical anvil cloud area feedback of  $-0.23 \pm 0.08 \text{ W m}^{-2} \text{ K}^{-1}$  (1-sigma) from their  
1637 study (note this uncertainty only includes sampling errors).

1638

1639 Other observational studies have tried to estimate the net radiative effect of changing anvil clouds.  
1640 While a negative feedback was also found in Choi et al. (2017), some studies have found tropical  
1641 high clouds produce neutral (Zelinka and Hartmann, 2011) or even slightly positive cloud radiative  
1642 feedbacks (Lin et al., 2002; Chambers et al., 2002). While the results from Williams and  
1643 Pierrehumbert (2017) are given more weight because they use the most accurate radiation budget  
1644 measurements covering the most recent analysis period, we also recognize the considerable  
1645 uncertainties associated with the observational estimates, the differing quantities measured in  
1646 various studies, and the correspondence between short-term observed and long-term climate  
1647 feedbacks. Accordingly we assign a maximum likelihood value of  $-0.20 \text{ W m}^{-2} \text{ K}^{-1}$ , with a large  
1648 standard deviation of  $0.20 \text{ W m}^{-2} \text{ K}^{-1}$ . Our assessment would be consistent with the moderately  
1649 stabilizing negative cloud feedbacks found in Williams and Pierrehumbert (2017) but does not rule  
1650 out neutral cloud feedbacks, since a value of zero is within one standard deviation of our maximum  
1651 likelihood value. Note that the effect we find based on recent observational analyses is an order of  
1652 magnitude smaller than the strongly stabilizing cloud feedbacks once suggested by Lindzen et al.  
1653 (2001) and Lindzen and Choi (2011).

### 1655 3.3.4 Land cloud feedback

1656

1657 Preferential warming of land surfaces is expected to lead to relative humidity reductions,  
1658 particularly where the climatological temperatures are warm, i.e., the tropics, subtropics, and mid-  
1659 latitudes in summer (Manabe et al., 1981; Findell and Delworth, 2005; Sherwood and Fu, 2014).  
1660 The primary explanation for this relative humidity reduction is that the combination of surface  
1661 evaporation and horizontal water vapor transport from oceans does not increase as fast with  
1662 warming as Clausius-Clapeyron requires to keep local relative humidity constant (Sherwood and  
1663 Fu, 2014; Scheff and Frierson, 2015; Byrne and O’Gorman, 2016). This is mainly because the  
1664 surface temperature warms considerably more over land compared with the ocean (Joshi et al.,  
1665 2008; Byrne and O’Gorman, 2013a), a robust result of GCM warming simulations. Theoretically,  
1666 the greater warming over land may result in large part from atmospheric dynamics (Sobel and  
1667 Bretherton 2000) maintaining constant convective instabilities between ocean and land leading to  
1668 nearly the same changes in surface moist static energy (Byrne and O’Gorman, 2013b; Sherwood  
1669 and Fu, 2014). Secondary contributions to relative humidity reductions with warming may come  
1670 from reductions in soil moisture (Manabe and Wetherald, 1987; Berg et al., 2016) or regional  
1671 circulation changes such as the poleward expansion of subtropical dry zones (Scheff and Frierson,  
1672 2012). (Note that effects on relative humidity and clouds from the response of plant stomata to CO<sub>2</sub>  
1673 increases contribute to rapid radiative adjustment to CO<sub>2</sub> (section 3.2.1) and not the temperature-  
1674 mediated changes discussed here.)

1675

1676 The consequence of the relative humidity reductions is a widespread reduction of cloudiness over  
1677 warm land regions that is very robustly simulated by GCMs (Bretherton et al., 2014; Kamae et al.,  
1678 2016). Decreasing cloudiness due to decreases in relative humidity is also theoretically expected  
1679 and supported by observations of low clouds over land (Del Genio and Wolf, 2000; Zhang and  
1680 Klein, 2013). In GCMs, the contribution from cloud amount reductions over land to the global mean  
1681 cloud feedback is  $+0.08 \text{ W m}^{-2} \text{ K}^{-1}$  with standard deviation  $0.03 \text{ W m}^{-2} \text{ K}^{-1}$ , based upon the  
1682 calculations of Zelinka et al. (2016) applied to all available models. While clouds at all vertical  
1683 levels of the atmosphere decrease, the majority of this net cloud feedback comes from the  
1684 reduction in low clouds which increases the absorption of solar radiation but does not appreciably  
1685 affect the emission to space of long-wave radiation. Apart from GCMs, observations show  
1686 decreases in surface relative humidity over recent decades (Willett et al., 2018) which are  
1687 consistent with those predicted by the primary explanation given the observed amount of ocean  
1688 warming (Byrne and O’Gorman, 2018). These relative humidity reductions may be attributed to  
1689 anthropogenic forcing of the climate system (Douville and Plazzotta, 2017).

1690

1691 In summary, we assess this feedback to be credible and assign a maximum likelihood value of  
1692  $+0.08 \text{ W m}^{-2} \text{ K}^{-1}$  which matches the mean of available GCM predictions. However, we assign a  
1693 higher standard deviation,  $0.08 \text{ W m}^{-2} \text{ K}^{-1}$ , to reflect the fact that GCMs have substantial biases in  
1694 land climate which indicates some structural uncertainty. In particular, GCMs markedly  
1695 underestimate the relative humidity, cloudiness and precipitation and overestimate surface  
1696 temperature during the warm season (Ma et al., 2014; Morcrette et al., 2018). Furthermore, biases  
1697 in the mean climate appear to project upon climate responses to warming at least in middle  
1698 latitudes (Cheruy et al., 2014; Lin et al., 2017).

1699

### 1700 **3.3.5 Mid-latitude marine low-cloud amount feedback**

1701  
1702 Middle (30-60°) latitude cloud coverage is strongly modulated by baroclinic disturbances in the  
1703 storm track. A positive extratropical cloud feedback has long been expected to accompany global  
1704 warming owing to the poleward shift of the storm track and its attendant clouds towards regions of  
1705 less incoming solar radiation. In apparent support of this notion, trends in satellite and ground-  
1706 based cloud observations indicate poleward shifts of middle latitude cloud maxima and/or  
1707 subtropical cloud minima (Bender et al., 2012; Eastman and Warren, 2013; Marvel et al., 2015;  
1708 Norris et al., 2016), but the exact magnitude of these shifts is uncertain owing to observational data  
1709 artifacts that can introduce spurious trends. Moreover, the observed sensitivity of net cloud  
1710 radiative effects to interannual variations in jet latitude appears surprisingly small, owing to  
1711 compensation between high- and low-cloud responses. Namely, whereas upper-level clouds tend  
1712 to move poleward with the jet, low-level clouds (which can be more tied to surface conditions) do  
1713 not. Rather, enhanced subsidence, stability, and cold advection lead to increased low-cloud  
1714 coverage in regions vacated by higher clouds (Grise and Medeiros, 2016; Tselioudis et al., 2016;  
1715 Zelinka et al., 2018). Thus, it is unlikely that substantial cloud feedbacks arise from storm track  
1716 shifts (Grise and Polvani, 2014; Ceppi and Hartmann, 2015).

1717  
1718 Mid-latitude, low-cloud responses could also be driven by thermodynamic processes similar to  
1719 those governing the tropical low cloud response (Qu et al., 2014; Narenpitak et al., 2017). Indeed,  
1720 Norris and Iacobellis (2005) infer a positive mid-latitude cloud feedback based on observed  
1721 variations in mid-latitude cloud properties with temperature, while controlling for other  
1722 meteorological influences. Zhai et al. (2015) and McCoy et al. (2017) also infer a positive feedback  
1723 from observed variations of low clouds with temperature in the 30-40° latitude band.

1724  
1725 GCMs consistently predict reduced cloud fraction throughout the mid-latitude troposphere with  
1726 warming (Figure 5 a), and the reduction in low cloud amount induces a strong positive feedback  
1727 (Figure 5 e). Modeled mid-latitude net cloud-radiative effect anomalies attributable to future jet  
1728 shifts are small compared to the total predicted radiative change (Kay et al., 2014; Ceppi and  
1729 Hartmann, 2015; Wall and Hartmann, 2015), consistent with the observational results above. A  
1730 positive mid-latitude cloud feedback may be caused by SST increases and stability decreases, but  
1731 further study is needed to quantify the dependence of low cloud on SST and inversion strength or  
1732 other cloud controlling factors at mid-latitudes before making confident attribution statements.

1733  
1734 In summary, despite the apparent lack of a substantial cloud feedback from poleward shifts of the  
1735 mid-latitude storm track, observed variations of mid-latitude low clouds (Norris and Iacobellis,  
1736 2005; Zhai et al., 2015; McCoy et al., 2017) provide qualitative support to the strong positive mid-  
1737 latitude low cloud amount feedbacks robustly predicted by GCMs. Based upon the calculations of  
1738 Zelinka et al. (2016) applied to all available models, the GCM contribution to global feedback from  
1739 ocean areas between 30-60° latitude (27% of the globe) has a mean of  $0.12 \text{ W m}^{-2} \text{ K}^{-1}$  with a  
1740 standard deviation of  $0.08 \text{ W m}^{-2} \text{ K}^{-1}$ . Extrapolating the observationally derived tropical low cloud  
1741 feedback (Klein et al., 2017) to the mid-latitude oceans after accounting for reduced insolation  
1742 yields a feedback between  $0.08$  and  $0.20 \text{ W m}^{-2} \text{ K}^{-1}$ , depending upon whether the observed  
1743 tropical low cloud sensitivities are assumed to apply to the entire 30-60° latitude band or only to the  
1744 30-40° latitude band investigated in Zhai et al. (2015) and McCoy et al. (2017). Considering both  
1745 the GCM and observational estimates, we assign a maximum likelihood value of  $+0.12 \text{ W m}^{-2} \text{ K}^{-1}$ ,  
1746 consistent with the GCM mean and observational estimates, but increase the standard deviation to

1747 0.12 W m<sup>-2</sup> K<sup>-1</sup> to reflect uncertainty in GCM simulations of marine low cloud and the range of  
1748 observational estimates.  
1749

### 1750 **3.3.6 High-latitude low-cloud optical depth feedback**

1751  
1752 Cloud optical depth (opacity) can increase due to either smaller cloud particles (for a given cloud  
1753 water path) and/or increases in water path (Stephens, 1978). Several mechanisms that favor  
1754 increased optical depth with warming have been proposed. First, a shift of cloud ice to liquid upon  
1755 warming leads to brighter clouds, as a given amount of cloud water is more reflective if distributed  
1756 among liquid droplets, which tend to be smaller, rather than fewer large ice crystals (Storelvmo et  
1757 al., 2015). Second, increases in the liquid fraction of condensate can inhibit precipitation (Klein et  
1758 al., 2009; Solomon et al., 2011), resulting in clouds with more total water content. Third, the  
1759 adiabatic water content of clouds increases with temperature following fundamental  
1760 thermodynamic theory (Betts and Harshvardan, 1987). Opposing these effects, liquid clouds may  
1761 be thinned via increased entrainment drying with warming due to the greater saturation deficit  
1762 (Blossey et al., 2013; Bretherton 2015; Bretherton and Blossey, 2014; Bretherton et al., 2013;  
1763 Brient and Bony 2013; Rieck et al., 2012; Sherwood et al., 2014), though this mechanism has only  
1764 been investigated for subtropical low clouds, and its relevance for cloud thickness as opposed to  
1765 cloud fraction is uncertain.

1766  
1767 GCMs simulate a negative feedback poleward of about 40° latitude from optical depth increases,  
1768 especially for low clouds (Figures 5 d-e). GCMs also exhibit a strong correspondence across  
1769 time scale for the temperature sensitivities of high-latitude cloud optical depth and liquid water path  
1770 (i.e., an emergent constraint, Gordon and Klein, 2014; Ceppi et al., 2016), suggesting that present-  
1771 day observations can be used to assess this feedback. Terai et al. (2016) inferred a shortwave low  
1772 cloud optical depth feedback of +0.24 W m<sup>-2</sup> K<sup>-1</sup> averaged between 40-70° of both hemispheres by  
1773 quantifying the sensitivity of low cloud optical depth to surface temperature in Moderate Resolution  
1774 Imaging Spectroradiometer satellite observations. In an independent analysis also using these  
1775 observations, Ceppi et al. (2016) derived a SW cloud optical depth feedback of -0.35 W m<sup>-2</sup> per  
1776 degree of 850-500 hPa temperature change averaged over 45-60°S. Re-normalizing by global  
1777 surface warming and accounting for the fact that the feedback is weaker in the NH yields a value of  
1778 -0.20 W m<sup>-2</sup> K<sup>-1</sup>. Assuming that these values also apply to the 40-70° latitude band (30% of the  
1779 globe) yields values of -0.06 W m<sup>-2</sup> K<sup>-1</sup> (Ceppi et al., 2016) and +0.07 W m<sup>-2</sup> K<sup>-1</sup> (Terai et al.,  
1780 2016). Quantitative differences in these results likely arise from differences in cloud types analyzed  
1781 and in the predictors used in deriving cloud optical depth sensitivities. Guided by these two studies,  
1782 we assign the maximum likelihood value for the high-latitude low cloud optical depth feedback to  
1783 0.0 W m<sup>-2</sup> K<sup>-1</sup>. The standard deviation of the likelihood function we assign to 0.10 W m<sup>-2</sup> K<sup>-1</sup>, which  
1784 allows for additional uncertainties beyond these two studies.

1785  
1786 This assessed feedback value is consistent with observational evidence suggesting that the  
1787 negative high latitude optical depth feedback simulated by many GCMs is too strong, likely due to  
1788 an exaggerated phase change feedback. In GCM experiments in which mean-state super-cooled  
1789 liquid water content more closely matches observations (Tan et al., 2016; Frey and Kay, 2018), the  
1790 negative SW optical depth feedback at high latitudes is weakened considerably. This negative  
1791 feedback has also weakened in some CMIP6 models, possibly related to improvements in mean-  
1792 state cloud phase distribution (Zelinka et al., 2020).  
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### 3.4 Process assessment of $\lambda$ and implications for $S$

Sections 3.2 and 3.3 have assessed the process evidence and assigned a Gaussian prior for  $\Delta F_{2xCO_2}$  and Gaussian likelihoods for individual climate feedbacks. Table 1 records the values of these terms and which lines of process evidence were used in their derivation.

According to eq. (18), the climate feedback parameter  $\lambda$  is equal to the linear sum of individual feedbacks. We further assumed that the total cloud feedback can be written as a linear sum of the individual cloud type feedbacks we assessed in section 3.3. Linearity of radiative feedbacks has been established (Wetherald and Manabe, 1980; Zhang et al., 1994; Colman and McAvaney, 1997; Mauritsen et al., 2013), although independence is another matter (see below). We formulate a Gaussian PDF for  $\lambda_{clouds}$  by adding the standard deviations for the individual cloud feedbacks in quadrature (assuming independent and uniform  $\lambda_i$  priors), and similarly, formulate a PDF for  $\lambda$  by adding the standard deviations of all feedbacks in quadrature (cf. eq. 13). Note this manner of combining feedbacks is valid only for the Baseline prior (see section 2.3). The resulting PDF for the total cloud feedback is  $N(+0.45, 0.33)$  (Table 1, Figure 7). Relative to the mean cloud radiative effect of around  $-20 \text{ W m}^{-2}$  in today's climate (Loeb et al., 2018), a cloud feedback of  $+0.45 \text{ W m}^{-2} \text{ K}^{-1}$  is equivalent to a  $\sim 2\%$  decrease in the net radiative effect of clouds for every K of temperature increase. Interpreting standard deviations as uncertainty, the total cloud feedback has the largest uncertainty relative to the other feedbacks (Planck, water vapor + lapse rate, surface albedo, atmospheric composition and stratospheric), just as it has in past assessments. In addition, quadrature summing of our assessed values shows that the uncertainty from all high cloud types combined is approximately equal to that of all low cloud types combined, indicating that future research is needed to improve the physical understanding of both high and low clouds.

Our PDF for  $\lambda$  is  $N(-1.30, 0.44)$  (Table 1, Figure 8a). Also assuming the prior on  $\Delta F_{2xCO_2}$  is independent from  $\lambda$ , the PDF of  $S$  using only process evidence can be derived (Figure 8c). The 50% percentile (median) of the  $S$  PDF occurs at 3.1 K, with the 17% and 83% percentiles at 2.3 K and 4.6 K. The asymmetric shape to the  $S$  PDF results from taking the inverse of the symmetric  $\lambda$  PDF following eq. (4) and the fact that in relative terms,  $\lambda$  is much more uncertain than  $\Delta F_{2xCO_2}$  (Roe and Baker, 2007). This implies that shifting the  $S$  PDF downward would require the identification of an unknown negative feedback much larger in magnitude than the unknown positive feedback that would be required to shift the  $S$  PDF upward by an equal amount (Schlesinger, 1989). Equivalently, the process assessment constrains the lower bound of  $S$  more tightly than its upper bound.

One may question our assumption of independence between  $\Delta F_{2xCO_2}$  and  $\lambda$ , as well as amongst likelihoods for all feedbacks except those for water vapor and lapse rate which we treat together in Table 1. Of particular importance is a significant anti-correlation between  $\Delta F_{2xCO_2}$  and  $\lambda$  in GCMs (Andrews et al., 2012a; Webb et al., 2013), which acts to reduce CMIP5 inter-model spread of  $S$  by about 0.6 K relative to what would be anticipated if these were uncorrelated (Andrews et al., 2012a; Caldwell et al., 2016). This anti-correlation cannot be explained as an artifact of the Gregory method for calculating  $\Delta F_{2xCO_2}$  and  $\lambda$  (Gregory et al., 2004) as it is seen in GCM experiments with both realistic and idealized configurations (e.g., fixed SST with globally uniform SST increases of 4 K) (Ringer et al., 2014). It is also seen in ensembles of untuned perturbed-parameter versions of single models as well as ensembles of tuned GCMs (Webb et al., 2013). A compensation between cloud feedback and adjustment is found to be the direct cause of this  $\Delta F_{2xCO_2}$  -  $\lambda$  covariance (Ringer et al., 2014; Chung and Soden 2017), but covariance exists even



1842 between feedbacks (Huybers, 2010; Caldwell et al., 2016; McCoy et al., 2016). Unlike the case of  
1843 the water vapor and lapse rate anti-correlation, the mechanisms behind feedback covariances are  
1844 generally not understood although new research attempts to explain these issues (McCoy et al.,  
1845 2016). In conclusion, because these GCM covariances are not understood and initial analyses  
1846 suggest that they are weaker in the CMIP6 model ensemble (Zelinka et al., 2020), we  
1847 conservatively overlook the anti-correlation found in some GCMs, leading to a somewhat broader  
1848 overall uncertainty. But given the potential of feedback and forcing anti-correlations to reduce the  
1849 overall uncertainty in  $S$  calculated from individual feedbacks and forcing, it should be a high priority  
1850 for future research to determine the physical basis of these relationships and their relevance for  
1851 the real world.  
1852

### 1853 **3.5 Constraints from observations of global inter-** 1854 **annual radiation variability**

1855  
1856 A significant concern with our primary approach is whether we have recognized all important  
1857 feedbacks, i.e., whether there could be large missing feedbacks, particularly from any cloud types  
1858 that we did not assess. While GCMs indicate that the cloud feedbacks we haven't assessed are  
1859 small in magnitude having a mean and standard deviation of  $-0.02$  and  $0.15 \text{ W m}^{-2} \text{ K}^{-1}$ ,  
1860 respectively (not shown), a more powerful way to address this concern is by considering the  
1861 studies that have attempted to constrain the total climate feedback parameter  $\lambda$  via analysis of  
1862 observed inter-annual variability in globally-averaged TOA net radiation. The premise is that inter-  
1863 annual temperature fluctuations will have had the chance to activate feedbacks from any and all  
1864 cloud types. This premise is plausible (a) because the warming correlated with inter-annual  
1865 fluctuations of global mean temperature is global in nature, occurring in both the tropics and  
1866 extratropics (Dessler, 2013), and (b) because the inherent timescales of all clouds are from  
1867 minutes to at most a few days, and thus there is more than enough time available for clouds to  
1868 respond to the inter-annual changes in temperature.  
1869

1870 After accounting for changes in forcing, linear regression of observed anomalies in global net  
1871 radiation  $\Delta N$  on observed anomalies in global surface temperature  $\Delta T$  provides an empirical  
1872 estimate of  $\lambda$  according to (3.1). The reviews of Forster (2016) and Loeb et al. (2016) report that  
1873 the studies with the most robust methods and recent radiation data found  $\lambda$  values ranging from  
1874  $-1.13 \pm 0.5$  to  $-1.25 \pm 0.5 \text{ W m}^{-2} \text{ K}^{-1}$  (1-sigma) (Murphy et al., 2009; Dessler, 2013, Donohoe et  
1875 al., 2014; Trenberth et al., 2015). Dessler (2013) additionally estimated values of individual  
1876 feedbacks in (3.1) such as the water vapor, lapse rate, cloud, and surface albedo feedbacks, which  
1877 we have discussed in section 3.2 and displayed in Figure 4 .  
1878

1879 Empirically estimated feedback values change somewhat depending on the regression method  
1880 and the observational datasets (Forster, 2016; Loeb et al., 2016; Proistosescu et al., 2018),  
1881 although differences are generally small (Dessler and Loeb, 2013, Zhou et al., 2013). Larger  
1882 changes occur when the regression is calculated over different time periods; Loeb et al. (2016)  
1883 report feedback values of  $-1.18 \pm 0.58$  but  $-0.27 \pm 0.47 \text{ W m}^{-2} \text{ K}^{-1}$  (1-sigma) for the 2001–2013  
1884 and 2001–2015 periods, respectively. Considering the range of uncertainty, these values are not  
1885 inconsistent with each other, and taken together they provide a similar mean and spread as our  
1886 PDF for  $\lambda$  from combining feedbacks (Figure 8 a). Because the latter used Dessler's (2013)  
1887 observed estimates of the clear-sky feedbacks in section 3.2, this comparison only tests the  
1888 consistency of our assessment of the total cloud feedback with Dessler's estimate which is  $+0.49 \pm$

1889 0.35 W m<sup>-2</sup> K<sup>-1</sup> (1-sigma) for the 2000–2010 period. This value overlaps well with the PDF for the  
1890 total cloud feedback (Table 1). However, estimates for periods including more recent years are  
1891 more positive (Dessler, personal communication).

1892  
1893 A fundamental question is whether feedbacks diagnosed from short time scales are representative  
1894 of the long-term feedbacks (Forster, 2016; Loeb et al., 2016; Proistosescu et al., 2018). Because  
1895 many atmospheric processes involved in climate feedbacks evolve on short time scales (hours to  
1896 weeks) and thus quickly adjust to more slowly changing boundary conditions such as surface  
1897 temperature, the radiative response to warming of all climate feedback processes might be  
1898 invariant from inter-annual to long-term time scales. However, to the extent that unrelated radiation  
1899 anomalies drive surface temperature anomalies, the climate feedback parameter diagnosed from  
1900 the relationship between anomalies in radiation and temperature might be biased high (Spencer  
1901 and Braswell, 2010). Calculations though suggest that this is a relatively minor concern as the  
1902 dominant source of inter-annual variability in temperature is from ocean forcing and not radiation  
1903 (Dessler, 2011; Proistosescu et al., 2018).

1904  
1905 Another aspect of this question is whether the spatial patterns of surface temperature change seen  
1906 in inter-annual variability provoke global-mean responses similar to those of the smoother pattern  
1907 anticipated from long-term CO<sub>2</sub> warming (Proistosescu et al., 2018). For example, low-cloud and  
1908 lapse-rate feedbacks depend strongly upon the pattern of surface temperature change (sections  
1909 3.3.2 and 4.2). The warming pattern from inter-annual variability is dominated by El Niño variability  
1910 within the tropics but also has warming at higher latitudes (Dessler 2013). As such, while not as  
1911 uniform, the inter-annual warming pattern exhibits some similarity to the long-term warming pattern  
1912 projected by GCMs which has often been called “El Niño-like” (Meehl and Washington, 1996; Yu  
1913 and Boer, 2002; Vecchi et al., 2008, also see section 4.2 ). Most notably at both long-term and  
1914 inter-annual time-scales, there is greater warming in the central and eastern Pacific relative to that  
1915 in the western Pacific and this favors positive low-cloud and lapse rate feedbacks. Given the  
1916 similarity in spatial pattern of surface temperature change, global averages of the feedbacks  
1917 inferred from inter-annual time-scales might be expected to exhibit some similarity to those  
1918 associated with long-term warming.

1919  
1920 GCMs can be used to test the similarity between global feedbacks at different time scales. Colman  
1921 and Hanson (2017) examined individual feedbacks in CMIP5 models and found that inter-annual  
1922 values diagnosed from pre-industrial control simulations were generally consistent with values in  
1923 response to climate warming for the water vapor, lapse rate, surface albedo, and total cloud  
1924 feedbacks (Figure 9 ). A general consistency also applies to decadal time-scale feedbacks  
1925 derived from pre-industrial control simulations (Colman and Hanson, 2018). In particular,  
1926 cloudiness exhibits similar spatial responses to increasing temperature at inter-annual and long-  
1927 term time scales (i.e. an emergent constraint is present), with inter-annual and long-term  
1928 feedbacks well correlated across models, albeit with a slope different than unity (Zhou et al., 2015).  
1929 The consistency of GCM climate feedbacks between inter-annual variability and long-term  
1930 warming supports the use of the inter-annual observations in assessing climate feedbacks. We  
1931 conclude that the chances of major errors or omissions in our assessment are reduced, particularly  
1932 for our assessment that the total cloud feedback is positive, since we do not find any evidence of  
1933 missing feedbacks in the interannual variability.

1934  
1935 In summary, examining global-mean radiation variations provides a similar central estimate of  $\lambda$   
1936 and comparable spread to that obtained from combining feedbacks. On its own, there is a danger  
1937 that our combining-feedback approach could miss unassessed feedbacks—particularly from

1938 clouds—and to account for this quantitatively we should broaden the PDF given in section 3.4  
1939 (without shifting its central value). On the other hand, the global-mean satellite evidence in  
1940 principle includes all rapid feedbacks including those from the clouds we didn’t assess. Moreover it  
1941 is largely independent from the individual process evidence; bear in mind that although a similar  
1942 approach was used in section 3.2 to help constrain clear-sky feedbacks, the main concern is  
1943 clouds. Therefore updating the PDF from section 3.4 with this additional evidence would make the  
1944 PDF narrower, again without shifting its central value. In light of these opposing considerations,  
1945 both of which are hard to quantify precisely, we judge the result obtained in section 3.4 to be a fair  
1946 representation of the overall probabilities given all evidence, and will be adopted in this  
1947 assessment.  
1948

### 1949 **3.6 Emergent constraints on S from present-day** 1950 **climate system variables**

1951  
1952 In recent years, a wide variety of present-day climate system variables including clouds, water  
1953 vapor, precipitation, radiation, circulation and temperature, has been identified with skill at  
1954 predicting S through emergent constraints (Table 2). Emergent constraints on S also exist  
1955 related to the rate of warming since 1970 and tropical temperature changes during the Last Glacial  
1956 Maximum and mid-Pliocene warm period, and are discussed elsewhere (sections 4.1.3, 5.2.4 and  
1957 5.3.1, respectively). The common occurrence of variables related to clouds, and tropical low clouds  
1958 in particular, is not surprising given the leading role of the shortwave cloud feedback from tropical  
1959 low-clouds in explaining S variance in CMIP ensembles (Caldwell et al., 2018; Qu et al., 2018).  
1960 Several constraints involve the short-term temperature sensitivity of low-clouds, which is likely  
1961 related to their long-term feedback, and perhaps total  $\lambda$ , if the relationship between clouds and  
1962 their cloud-controlling factors were constant across time-scales (section 3.3.2). Indeed, if total  $\lambda$   
1963 were constant, the fluctuation-dissipation theorem suggests that the amplitude and autocorrelation  
1964 of inter-annual temperature variability would depend on  $\lambda$  (among other factors), such that  
1965 observations of temperature variability might constrain  $\lambda$  and hence S. This is the physical  
1966 explanation given for the temperature variability emergent constraint of Cox et al. (2018).  
1967

1968 It is a relatively new activity to constrain future climate using the inter-model spread of a GCM  
1969 ensemble and observations of a correlated present-day climate system variable. Hall et al. (2019)  
1970 give a framework to consider this activity and provide “confirmation indicators” to gauge the  
1971 trustworthiness of an emergent constraint. This is helpful as spurious predictors may be present in  
1972 climate model ensembles due to their small size (Caldwell et al., 2014).  
1973

1974 One confirmation indicator is out-of-sample testing, which can partially be achieved by comparing  
1975 results across generations of CMIP ensembles. Caldwell et al. (2018) found that four out of five  
1976 emergent constraints constructed using the earlier CMIP ensembles had no skill at predicting S in  
1977 the CMIP5 ensemble. It will be interesting to see how many of the constraints in Table 2 will  
1978 have predictive capability in the new CMIP6 ensemble.  
1979

1980 Another confirmation indicator is having a verified and plausible mechanism explaining the  
1981 constraint. Although the proponents of each constraint have offered explanations, verifying them is  
1982 difficult. One test is whether the present-day predictor is also correlated with available measures of  
1983 the specific climate feedback identified in the physical explanation (Caldwell et al., 2018).  
1984 Unfortunately, the lack of specificity in the physical explanations for many constraints limits the

1985 applicability of this test. In this assessment, we take the viewpoint that all emergent constraints  
1986 have some (even if limited) information about  $S$ .  
1987  
1988 The application of the same mathematical approach to all constraints facilitates comparison of their  
1989 predictions. Column 5 of Table 2 reports a central estimate of  $S$  derived for 17 emergent  
1990 constraints. This estimate is calculated from the ordinary least squares linear regression of  $S$  on  
1991 the present-day climate system variable evaluated at its observed value using the data for the  
1992 combined CMIP3/CMIP5 ensemble compiled in Caldwell et al. (2018), and hence, represents the  
1993 maximum-likelihood value of  $S$  assuming a linear relationship. More advanced methods of  
1994 determining the predictand  $S$  from emergent constraint relationships are discussed in Bowman et  
1995 al. (2018), Schneider (2018), Williamson and Sansom (2019), and Brient (2020).  
1996  
1997 All emergent constraints predict this maximum-likelihood value of  $S$  to lie between 2.8 K and 4.2 K,  
1998 consistent with the statements given in the original papers (Column 4 of Table 2). A general  
1999 tendency for greater agreement with observations of present-day climate system variables for  
2000 GCMs with  $S$  values in this range was also found in related model-weighting studies using  
2001 observations of multiple present-day climate system variables (Murphy et al., 2004; Knutti et al.,  
2002 2006; Huber et al., 2011; Brown and Caldeira, 2017).  
2003  
2004 Overall, these studies suggest that observations of a wide range of present-day climate system  
2005 variables are more consistent with  $S$  higher than 2.8 K. This consistency of predictions suggests  
2006 that it may be possible to form a single likelihood function to represent this evidence. We proceed  
2007 approximately, as there is no established literature on how to combine constraints, particularly  
2008 when dependencies between constraints may exist (Hall et al., 2019). (See Bretherton and  
2009 Caldwell (2020) for a first attempt to combine the predictions from multiple emergent constraints.)  
2010  
2011 First, we consider these emergent constraints using present-day climate system variables to be  
2012 constraints on the climate feedback parameter  $\lambda$ , rather than  $S$ , since the present-day climate  
2013 system variables are not directly a function of  $\text{CO}_2$  variations and are more closely related to  
2014 climate feedback processes than  $S$  itself. To determine their predictions for  $\lambda$ , we calculate central  
2015 estimates for  $\lambda$  from the regression of  $\lambda$  on the present-day climate system variables in the identical  
2016 way as for  $S$  (Column 6 of Table 2). The central values of  $\lambda$  locate on average at  $-1.01 \text{ W m}^{-2}$   
2017  $\text{K}^{-1}$ , and this average does not vary by more than  $0.05 \text{ W m}^{-2} \text{ K}^{-1}$  if one excludes the emergent  
2018 constraints that don't pass the ensemble robustness and physical mechanism tests of Caldwell et  
2019 al. (2018). We therefore assign  $-1.01 \text{ W m}^{-2} \text{ K}^{-1}$  as the mean of a Gaussian likelihood function for  
2020  $\lambda$  based upon this emergent constraint evidence.  
2021  
2022 The second step of assigning a standard deviation to the likelihood function is more complicated.  
2023 The uncertainties in  $\lambda$  calculated from the errors in the linear regression fit and the observational  
2024 uncertainty in the present-day climate system variable are insufficient to characterize the structural  
2025 uncertainty, especially for  $\lambda$  values outside the range seen in the available GCMs. Several  
2026 considerations favor assigning a larger width to the likelihood function. First, the authors of  
2027 individual constraints may have consciously or unconsciously chosen details of their present-day  
2028 climate system variable to optimize its correlation with  $S$  over the GCMs they were examining,  
2029 which results in an over-confident prediction. Furthermore, the emergent constraint approach  
2030 implicitly assumes that all other GCM characteristics relevant for  $\lambda$  except the present-day climate  
2031 system variable are unbiased and complete, and to the extent that this is not the case, predictions  
2032 could be biased (Klein and Hall, 2015). Finally, when compared with the individual feedback  
2033 approach, the emergent constraint approach appears less rigorous given the general lack of

2034 verified mechanisms and relative indirectness of the relationship between the present-day climate  
2035 system variable and a highly integrated quantity like the total climate feedback parameter  $\lambda$  which  
2036 is dependent on multiple feedbacks (Klein and Hall, 2015; Hall et al., 2019). (This is less of a  
2037 concern for emergent constraints for individual climate feedbacks.) With these considerations in  
2038 mind, we assign the Gaussian width of the likelihood function from emergent constraints to be  $0.6$   
2039  $\text{W m}^{-2} \text{K}^{-1}$ , a value  $\sim 40\%$  larger than the uncertainty in  $\lambda$  from the primary process approach  
2040 assessing individual feedbacks (section 3.4). The likelihood function from emergent constraints is  
2041 thus  $N(-1.01, 0.6)$  and illustrated in Figure 8 b. It indicates very low likelihood on the low end of  
2042  $S$  (large negative  $\lambda$ ), but much less constraint on the high end of  $S$  (small negative  $\lambda$ ).

2043  
2044 One may wonder how independent emergent constraints are from the primary approach, given that  
2045 both approaches use GCMs and in some cases the same present-day observational evidence  
2046 (particularly for tropical low clouds). One could perhaps treat the latter issue by only examining  
2047 those constraints using present-day climate system variables not already considered by the  
2048 primary assessment, but a common reliance on GCM simulations of present-day climate would  
2049 remain. Furthermore, while independent information is suggested by the fact that all emergent  
2050 constraints have a central estimate of  $\lambda$  smaller than that of the process central estimate of  $-1.30$   
2051  $\text{W m}^{-2} \text{K}^{-1}$ , the difference in predicted  $\lambda$  is not large compared to the overall uncertainty and could  
2052 be the result of a missing process biasing the prediction of either emergent constraints or the  
2053 individual feedbacks. Other arguments supporting independence are that the emergent constraint  
2054 and individual feedback methodologies are very different and that some emergent constraints use  
2055 present-day climate system variables not considered by the primary approach. We conclude that  
2056 the two approaches are not wholly dependent, but are also unlikely to be wholly independent.

2057  
2058 In summary, we consider the emergent constraints from present-day climate system variables to  
2059 offer evidence favoring  $S$  above  $2.8 \text{ K}$ . However, the evidence comes with a greater number of  
2060 issues than those affecting the primary approach. These issues are that: (a) many of these  
2061 emergent constraints for  $S$  are not confirmed with respect to either robustness to model ensemble  
2062 or a known physical mechanism, making it difficult to know how much confidence to give them; (b)  
2063 it is unclear whether the evidence from these emergent constraints is independent of the evidence  
2064 used in the primary approach to assess individual feedbacks; and, (c) we formulated a likelihood  
2065 function in an ad-hoc manner. While future work may address these issues, they currently warrant  
2066 a cautious approach to the treatment of these emergent constraints in the Bayesian analysis of  $S$ .  
2067 Accordingly, in section 7 we use the emergent constraint likelihood function only for a sensitivity  
2068 study, not for our Baseline calculation. In the sensitivity study, the emergent-constraint evidence is  
2069 assumed to be independent in order to explore its maximum impact.

2070  
2071

## 2072 **3.7 Summary**

2073  
2074 The climate sensitivity  $S$  is determined by the radiative forcing per  $\text{CO}_2$  doubling  $\Delta F_{2\times\text{CO}_2}$ , and the  
2075 sensitivity of top-of-atmosphere (TOA) net radiation to global-mean temperature (“total climate  
2076 feedback”),  $\lambda$ . In this section, we assessed the various lines of evidence—observations, theory,  
2077 GCMs, and process-resolving models—directly constraining these two quantities. The focus is on  
2078 physical processes that control the TOA energy balance via the global albedo and the greenhouse  
2079 effect.  $\Delta F_{2\times\text{CO}_2}$  is relatively well known and its direct component can be calculated from the  
2080 equations of radiative transfer using line-by-line models. Most uncertainty therefore comes from

2081 the climate feedback parameter  $\lambda$ , which is in turn the sum of contributions  $\lambda_i$  from a set of distinct  
2082 feedbacks.

2083  
2084 Among these distinct feedbacks, those due to clouds remain the main source of uncertainty in  $\lambda$ ,  
2085 although the uncertainty in the other feedbacks is still important. It follows from eq. ( 4) and the  
2086 relatively small uncertainty in other feedbacks and  $\text{CO}_2$  forcing that a negative feedback from  
2087 clouds is required to push  $S$  near or below 2 K. Moreover, this negative feedback must strengthen  
2088 nonlinearly to push  $S$  progressively lower, since  $dS/d\lambda \sim \lambda^{-2}$ . We find that a negative total cloud  
2089 feedback is very unlikely, and that there is sufficient evidence to effectively rule out the values of  $\lambda$   
2090 required to bring  $S$  below 1.5 K, thus placing a strong constraint against very low  $S$ .

2091  
2092 Carefully quantifying these inferences on a feedback-by-feedback basis and for the  $\text{CO}_2$  forcing  
2093 produces a process-based PDF for  $S$  which has its median value at 3.1 K, and the 17% and 83%  
2094 percentiles at 2.3 K and 4.6 K (Figure 8 c). This is based on Gaussian means and standard  
2095 deviations for  $\Delta F_{2\times\text{CO}_2}$  and each  $\lambda_i$  (Table 1), with broad prior probabilities and a priori  
2096 independence assumed for all quantities. Results are robust to sensitivity tests as discussed later  
2097 in section 7.3. This PDF still stands when accounting for (a) the additional constraint from separate  
2098 evidence from observations of global inter-annual radiation variability on  $\lambda$ , and (b) the additional  
2099 uncertainty associated with possible errors in identifying a complete set of feedbacks  $\lambda_i$ , the two of  
2100 which we take to roughly cancel out. In this sense, the total  $\lambda$  evidence from observations of inter-  
2101 annual radiation variability makes an important contribution even though it is not directly used in  
2102 the likelihood.

2103  
2104 Separately, emergent constraints on  $S$  based upon present-day climate system variables offer an  
2105 alternative, but not entirely independent approach to assess  $S$ , based upon exploiting the  
2106 relationship across a GCM ensemble between  $S$  and an observed present-day climate system  
2107 variable. By combining the evidence from the available constraints, we assess a separate  
2108 emergent constraint likelihood function for  $\lambda$  (Figure 8 b). Relative to the individual feedback  
2109 approach, the emergent constraint approach points towards a somewhat smaller  $\lambda$  and larger  $S$ ,  
2110 but with considerably less precision. It also comes with greater caveats necessitating a more  
2111 cautious treatment.

2112  
2113 Regardless of approach, the total cloud feedback is the key quantity driving the uncertainty, since  
2114 other feedbacks are well constrained by multiple lines of evidence supported by good basic  
2115 physical understanding. The cloud feedback is constrained mainly by summing up feedbacks  
2116 associated with different cloud regimes (section 3.3) but also by observable indicators of the total  
2117 global sensitivity (section 3.5). Over the past decade, the contribution to this feedback from tropical  
2118 marine low clouds has received the greatest attention due to its dominant contribution to the  
2119 spread in total cloud feedback across different GCMs (Bony and Dufresne, 2005). Recent research  
2120 has produced strong new evidence that these clouds provide positive feedback (section 3.3.2,  
2121 Figure 6 ). The reduced uncertainty surrounding this feedback component should be viewed as  
2122 a significant advance. However, uncertainty from other cloud responses remains significant and  
2123 possibly under-appreciated, thus worthy of greater attention in the future.

2124  
2125 The inferred positive total cloud feedback arises from several contributions. These include: (1) a  
2126 lifting of high cloud tops in warmer climates, as indicated by detailed numerical cloud simulations,  
2127 observed trends since the 1980s, climate models and expected from theory; (2) a dissipation of  
2128 tropical and mid-latitude marine low cloud, probably due to increased mixing of environmental air  
2129 into clouds as the climate warms, as indicated by observed cloud variability, and detailed

2130 numerical cloud simulations; and (3) a dissipation of warm-season low cloud over land due to  
2131 decreasing boundary layer relative humidity, as expected because land warms faster than oceans,  
2132 and as seen in observed humidity trends since the 1970s and in GCM simulations of warming.  
2133 Meanwhile, a sizeable negative feedback from clouds in tropical deep convection regions is  
2134 inferred from observations of inter-annual variability, but does not overwhelm the combined  
2135 positive feedbacks from rising high cloud tops and reduced low cloud cover. Separately, a negative  
2136 feedback due to transitions from ice to liquid in high-latitude clouds present in many GCMs is now  
2137 thought to be unrealistic. Interannual fluctuations in TOA energy balance, which reflect the net  
2138 effect of all cloud types, also point to a positive total feedback, suggesting that we haven't missed  
2139 any major feedbacks by assessing only a finite set of individual cloud types.

2140  
2141 To reconcile all of the above evidence with an overall *negative* feedback from clouds (which is  
2142 what would be required for  $S$  to be below 2 K given the other feedbacks, as discussed above)  
2143 would require multiple lines of evidence to have failed significantly for at least one cloud type. For  
2144 example, the low-cloud feedback could be negative only if observed sensitivities have been  
2145 misinterpreted, numerical cloud models are incorrect, the overall cloud feedback is near one end of  
2146 the range indicated by satellite data, and several emergent-constraint studies are incorrect. It  
2147 would be perhaps easier to imagine some unanticipated negative cloud feedback—but one that  
2148 simultaneously has not appeared in climate models, detailed cloud simulations, or observed  
2149 interannual variability or trends since 1979, so all lines of evidence would somehow have missed  
2150 this feedback. Similar multiple failures or misinterpretations of the evidence are probably required  
2151 to make the cloud feedback strongly positive enough to yield  $S$  significantly above 4.5 K, although  
2152 high  $S$  values are harder to rule out than low ones because  $S$  increases nonlinearly as positive  
2153 feedback increases.

2154  
2155 Several research trends have contributed to the recent progress in constraining  $S$  with process  
2156 understanding and are expected to contribute in the future:

- 2157  
2158 ● *Increased use of high-resolution process models such as large-eddy simulations and cloud-*  
2159 *resolving models to understand and constrain the feedbacks from a wider variety of cloud*  
2160 *types.* Increasing computational power allows for longer simulations of models with finer-  
2161 resolution and larger domains. For example, larger domains will permit LES to simulate the  
2162 impact of mesoscale circulations on the feedbacks from tropical marine low clouds (Nuijens  
2163 and Siebesma, 2019). Furthermore, short-simulations of global models with a horizontal  
2164 grid of  $O(1\text{ km})$  are now feasible. However, progress for cold clouds requires improved  
2165 representations of ice cloud microphysics.
- 2166  
2167 ● *Increased use of high-quality satellite observations with longer records to better constrain*  
2168 *climate feedbacks and the physical processes responsible for them.* Continuing cloud and  
2169 radiation observations from both passive and active sensors will reduce uncertainty in  
2170 feedbacks inferred from inter-annual variability and identify whether the feedbacks  
2171 exhibited through trends to the emerging warming are consistent with current  
2172 understanding. However, progress requires maintaining observations that are in danger of  
2173 disappearing at the end of current satellite missions. High-quality in-situ observations will  
2174 also help constrain key process uncertainties not amenable to satellite observations.
- 2175  
2176 ● *Increased analysis and understanding of climate feedbacks.* New diagnostics have  
2177 improved quantification and understanding of specific cloud feedbacks in both GCMs and  
2178 observations. Emergent constraints aid in identifying which present-day observations are of

2179 most value for inferring climate feedbacks. The interplay between GCM experimentation  
2180 and observational analysis has yielded important insights into topics such as the  
2181 relationships amongst climate feedbacks and their dependence on the spatial pattern of  
2182 warming. An important goal is to develop a more complete understanding of how the  
2183 climate feedbacks from short-term variability we observe relate to the feedbacks from long-  
2184 term forced climate change we seek.  
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## 4. Constraints from the Historical Climate Record

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What can we learn about climate sensitivity from the historical record of changes in global-mean temperature and the energy budget? The world has warmed by approximately 1 K since the 18th century (Allen et al., 2018). This warming is primarily attributable to the net effect of anthropogenic greenhouse gases and aerosols, but other external influences on the climate system and internal variability have also played a role (see assessment in Bindoff et al., 2013). A number of studies have estimated climate sensitivity based on observed changes in temperature and ocean heat uptake over a given period, along with the radiative forcing estimated from emissions inventories, observations, and climate models. Best estimates of climate sensitivity from such approaches range from 1-3 K and feature wide uncertainty ranges, particularly towards high values. More recent studies appear to have lowered the upper limits on sensitivity owing primarily to better constrained and stronger estimates of radiative forcing (see Knutti et al., 2017 and Forster, 2016 for reviews of recent progress), although recent wider ranges of aerosol forcing have put this narrowing into question (see below).

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It is not straightforward to infer a constraint on climate sensitivity from the historical record. Greenhouse gas forcing is not the only driver of historical climate change, and climate generates substantial variability. Also, as introduced in section 2.3, the climate is not in equilibrium with the forcing, and the feedbacks operating over the recent period may be different from those that determine sensitivity at equilibrium (see also Knutti et al., 2017). In section 4.1 we first diagnose climate sensitivity using the traditional approach, using equations (2) and (4), where we ignore the role of variability in TOA radiation ( $V$ ). We refer to the quantity thus estimated as  $S_{\text{hist}}$ . Section 4.2 then diagnoses a value of  $S$  employing the full equation (6), taking into account differences between radiative processes over the historical period compared to those over 150 years of a hypothetical  $\text{CO}_2$  quadrupling. Results are summarized and compared to earlier estimates in section 4.3.

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### 4.1 Inferring $S_{\text{hist}}$ from the historical climate record

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Most published estimates of  $S_{\text{hist}}$  based on the instrumental climate record directly or indirectly rely on a simple global energy balance model for the climate system (eq. 19) (see Gregory et al., 2002; Otto et al., 2013; Forster, 2016). Expressed in terms of the inferred climate sensitivity for the historical record,  $S_{\text{hist}}$ , combining eqs. (2) with (4) and neglecting internal variability  $V$ , the energy balance model becomes:

$$S_{\text{hist}} = \Delta F_{2\times\text{CO}_2} \Delta T / (\Delta F - \Delta N), \quad (19)$$

where  $\Delta T$  is the forced change in global mean surface temperature,  $\Delta F$  is the global mean radiative

2229 forcing, and  $\Delta N$  is the change in global mean downward net top-of-atmosphere energy imbalance.  
2230 Here,  $\Delta N$  can be measured directly either from the ocean heat content and/or from satellite  
2231 observations constrained by ocean heat content (Forster, 2016), and  $\Delta F_{2\times CO_2}$  is the radiative  
2232 forcing for  $CO_2$  doubling. The change  $\Delta$  is taken between the present day and a base period early  
2233 in the historical record, boundary conditions that will be discussed in detail in section 4.1.1.

2234  
2235 This inferred historical sensitivity  $S_{\text{hist}}$  should not be confused with the transient climate response  
2236 (TCR), which measures the transient warming of the Earth system before it reaches equilibrium.  
2237 By contrast, equation (19) attempts to use transient observations to estimate an equilibrium  
2238 quantity by accounting for the radiative imbalance  $\Delta N$  (Otto et al., 2013; Frame et al., 2006).

2239  
2240 Here, we assess the observationally based constraints on each of the three quantities:  $\Delta T$ ,  $\Delta F$  and  
2241  $\Delta N$  (section 4.1.1). We combine them with the PDF of  $\Delta F_{2\times CO_2}$  from Table 1 to calculate the  
2242 resulting likelihood for different values of  $S_{\text{hist}}$  assuming this simple energy balance model (section  
2243 4.1.2). We further investigate how such likelihoods change if the simple energy balance model (eq.  
2244 19) is modified by applying it to the changes in surface temperature and warming attributed to  
2245 greenhouse gases only, and by fitting models of varying complexity to observed spatial and  
2246 temporal patterns of climate change (section 4.1.3).

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## 2248 **4.1.1 Observationally based estimates, their inputs and uncertainties**

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2250 Observationally based changes and their uncertainties depend on which periods of the historical  
2251 record are used to estimate them. We define the “base period” from which anomalies are taken to  
2252 be the average over years 1861–1880 (1<sup>st</sup> Jan 1861 to 31 December 1880) because during this  
2253 time greenhouse gas levels were relatively close to (although not at) pre-industrial levels, there  
2254 were no large volcanic eruptions, and temperature records have adequate global coverage (see  
2255 Hawkins et al., 2017; Schurer et al., 2017). We also consider the alternative base period 1850-  
2256 1900 (1<sup>st</sup> Jan 1850 to 31 December 1900) which spans some major volcanic eruptions but reduces  
2257 the impact of internal climate variability due to its extended length. We define “present day” as the  
2258 average over years 2006–2018 (1<sup>st</sup> Jan 2006 to 31 December 2018), a period over which the  
2259 global energy imbalance was observed with relatively small uncertainty. We use differences  
2260 between these two periods to estimate  $\Delta T$ ,  $\Delta F$ ,  $\Delta N$  and produce constraints on  $S_{\text{hist}}$ .

2261

### 2262 **4.1.1.a: Forced surface temperature change ( $\Delta T$ )**

2263

2264 In order to estimate the global-mean temperature change  $\Delta T$ , we rely on gridded surface  
2265 temperature data. There are two recognized uncertainties associated with this observational  
2266 record. First, the surface network is sparse, particularly in the early portion of the historical record,  
2267 potentially leading to biased estimates of global mean temperature changes if observations are  
2268 missing over regions that are warming more (e.g., the Arctic) or less rapidly (e.g., the Southern  
2269 Ocean) than the global mean. Second, gridded temperature records generally blend sea surface  
2270 temperature (SST) over the oceans with near-surface air temperatures (SAT) over land, potentially  
2271 leading to an inconsistency, as  $S$  and  $S_{\text{hist}}$  are often assumed to be based on global mean SAT  
2272 changes. For example, using observations that are based on a combination of SAT and SSTs to  
2273 estimate global SAT changes can lead to a small underestimate of observed warming (Richardson  
2274 et al., 2016). The underestimate becomes more severe when missing coverage data is neglected  
2275 as well (Schurer et al., 2018). This then would lead to an underestimate of  $S$  based on SAT.

2276

2277 To account for coverage bias in the observations, we use the dataset developed by Cowtan and  
2278 Way (2014), which corrects for missing data in the observational network. To compare blended  
2279 SST/SAT data in observations with SAT-only trends in the energy budget, we add an offset term to  
2280 the “blended” observations. This term is derived from the difference between CMIP5 model SAT  
2281 fields and blended model SAT/SST fields (here, taken from the “xax” blended fields in Richardson  
2282 et al., 2016). Uncertainties in the resulting estimated observational SAT fields was calculated by  
2283 adding in quadrature the 5% to 95% uncertainties in the Cowtan and Way (2014) trends to the 5%-  
2284 95% range of the difference between SAT-only fields and blended model SAT/SST fields across all  
2285 CMIP5 RCP8.5 simulations, as the uncertainties were assumed to be independent and PDFs are  
2286 presumed Gaussian. The results were found to be insensitive to the choice of RCP scenario and  
2287 model. These estimates are detailed in Table 3 .

2288

2289 The relatively small uncertainties in Table 3 account for temporal error autocorrelation (e.g.,  
2290 Morice et al., 2012) but do not factor in internal variability. We quantify internal variability of global  
2291 mean temperature by considering all possible combinations of global temperature changes  
2292 between periods of the same length as used in our calculations (20 years to imitate years 1861-  
2293 1880, 51 years for years 1850-1900 and 13 years for 2006-2018) that are separated by more than  
2294 a century within unforced pre-industrial control simulations of 21 CMIP5 models, giving an average  
2295 standard deviation of 0.08 K and 0.07 K for the shorter and longer base periods, respectively.  
2296 Absent knowledge of whether this has contributed to or detracted from the observed warming, we  
2297 combine (in quadrature) the uncertainty in warming arising from internal variability with that arising  
2298 from instrumental uncertainties (presented in Table 3 ). This yields our overall estimates of  
2299 uncertainty of  $\pm 0.14$  K and  $\pm 0.12$  K (5%-95% ranges) for forced warming relative to 1861-1880  
2300 and 1850-1900, respectively (expressed as ranges in column 6 of Table 5). The main  $\Delta T$  used in  
2301 this analysis (e.g., Figure 11 ) is taken over 1861-1880 to 2006-2018 as 1.03 (0.89 K to 1.17K, 5  
2302 to 95% range) K (Table 5, line 1, column 6) due to the greater availability of data since 1861,  
2303 compared to 1850 and a relatively reduced level of volcanic activity.

2304

2305

#### 2306 **4.1.1.b Global energy imbalance change ( $\Delta N$ )**

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2308 Since the ocean accounts for most of the energy storage in the climate system, ocean heat uptake  
2309 dominates the change in global energy imbalance  $\Delta N$ . This means that a tight constraint on ocean  
2310 heat content changes can make the difference between a strong and very weak constraint on  
2311 climate sensitivity (e.g., Johannsen et al., 2016). Uncertainty in the dataset arises from incomplete  
2312 coverage, similar to the surface temperature discussed above, measurement techniques, and pre-  
2313 industrial reference period.

2314

2315 Here we estimate Earth’s global energy imbalance for 2006-2018 as  $0.8 \text{ W m}^{-2}$  (0.55 to 1.05, 5-  
2316 95% range). This global imbalance is estimated from the change in ocean heat content over time,  
2317 estimated using in-situ ocean observations with near-global ocean coverage (Johnson et al., 2016;  
2318 Purkey and Johnson, 2010; Desbruyères et al., 2016) combined with heat content changes  
2319 associated with ice sheet changes, sea ice loss, and land warming (Mouginot et al., 2019;  
2320 Schweiger et al., 2011; Shepherd et al., 2018; Zemp et al., 2019). It is dominated by the uptake of  
2321 heat by the ocean, which accounts for over 95% of the imbalance (Johnson et al., 2016). This  
2322 range of global energy imbalance is supported by other analyses of in-situ observations (Ishii et al.,  
2323 2017; Levitus et al., 2012; Cheng et al., 2017). It is also supported by several independent lines of  
2324 evidence suggesting that in-situ observations are accurate: (i) a high correlation between

2325 interannual variations in in-situ and satellite energy imbalance estimates (Johnson et al., 2016),  
2326 and (ii) the closure of the global sea-level budget (Chambers et al., 2017).

2327  
2328 The global energy imbalance assumed for both 1861-1880 and 1850-1900 base periods is  $0.2 \text{ W m}^{-2}$   
2329  $\text{m}^{-2}$  (0 to  $0.4 \text{ W m}^{-2}$ , 5 to 95% range), where these values are chosen to span those derived from  
2330 general circulation models (Lewis and Curry, 2015), energy balance modeling (Armour 2017), and  
2331 inferred ocean warming given observed SSTs using ocean GCMs (Gebbie and Huybers, 2019;  
2332 Zanna et al., 2019). As above, we quantify internal variability by considering all possible  
2333 combinations of global energy imbalance changes between periods of 20 (or 51) and 13 years in  
2334 length that are separated by more than a century within unforced detrended pre-industrial control  
2335 simulations of CMIP5 models, giving an average standard deviation of  $0.07 \text{ W m}^{-2}$  for both base  
2336 periods. The resulting value of the change in global energy imbalance is  $\Delta N = 0.6 \text{ W m}^{-2}$  (0.3 to 0.9  
2337 5% to 95% ranges assumed Gaussian, errors added in quadrature) for both base periods.

#### 2338 2339 **4.1.1.c Radiative forcing change ( $\Delta F$ )**

2340  
2341 The third important input is the total radiative forcing  $\Delta F$ . While often referred to as an observable  
2342 quantity, radiative forcing is not directly observable and must be derived from radiative transfer  
2343 models supported by estimates of rapid adjustments from climate models. While greenhouse  
2344 gases have dominated the forcing over the historical record, other forcing agents such as aerosols  
2345 and land-use change have played important roles as well. Even relatively small forcings can  
2346 matter: while volcanic forcing is short lived, cases where volcanic forcing is markedly different  
2347 between the beginning and end of a period analyzed could lead to long term climate variations as  
2348 seen in the last millennium (see PAGES-2k; Schurer et al., 2014). These effects can contaminate  
2349 constraints (Lewis and Curry, 2015) and errors in volcanic forcing could indirectly impact the  
2350 magnitude of the forced response (see Santer et al., 2015 and Johannsen et al., 2014). We chose  
2351 the reference periods at the beginning and end of the historical record to minimize this effect.  
2352 However, uncertainty in radiative forcing is dominated by the contribution from anthropogenic  
2353 aerosols, especially via their impact on clouds, which is relatively unconstrained by process  
2354 knowledge or direct observations (Bellouin et al., 2020). Here, to avoid circular reasoning, we try  
2355 not to use constraints on aerosol forcing based on idealized models fit to the historical record (see  
2356 review in Bindoff et al., 2013) and instead, we rely on bottom-up estimates of aerosol forcing from  
2357 models with comprehensive atmospheric physics.

2358  
2359 We obtain our prior PDF of  $\Delta F$  based on the approach of IPCC AR5 Chapter 8 (Myhre et al.,  
2360 2013), but using data extended through 2018 (Forster, 2016), and updating a number of forcing  
2361 components. First, we use the SARF formula (see section 3.2.1) for  $\text{CO}_2$ ,  $\text{CH}_4$  and  $\text{N}_2\text{O}$ , from Table  
2362 1 of Etminan et al. (2016). These SARF estimates increase  $\text{CH}_4$  forcing by 25% compared to AR5,  
2363 mainly to account for previously underestimated shortwave absorption (Etminan et al., 2016). To  
2364 this we add tropospheric adjustments and surface albedo estimated from the radiative kernel  
2365 analyses of Smith et al. (2018) to estimate a  $\text{CH}_4$  ERF over the historical period. Section 3.2.1  
2366 details a similar approach for  $\text{CO}_2$ . To estimate the evolution of  $\text{CO}_2$  ERF over the historical time  
2367 period, the ERF-to-SARF ratios for  $\text{CH}_4$  and  $\text{N}_2\text{O}$  are assumed to be constant over the period,  
2368 implying that the tropospheric and land-albedo adjustments scale with their SARF values.  
2369 Compared to the original AR5 time series, ozone ERFs and their time series are updated following  
2370 Myhre et al. (2017).

2371  
2372 Aerosol ERFs are taken from Bellouin et al. (2020), using the unconstrained PDF (Figure 8 of their  
2373 paper, with correction). The best estimate from Bellouin et al. (2020) utilizes top-down energy

2374 budget constraints and attribution studies, so to avoid circular arguments we only employ the  
 2375 unconstrained estimate which does not rely on detection and attribution studies to constrain  
 2376 aerosol through observed warming; or energy budget estimates. Compared to that of AR5, this  
 2377 PDF has a longer tail towards strong negative ERF, thus representing an increased uncertainty,  
 2378 with a peak around  $-0.8 \text{ Wm}^{-2}$  and a 5 to 95% range of  $-3.15$  to  $-0.37 \text{ Wm}^{-2}$ . This PDF is based  
 2379 on combining ranges of estimates from known physical processes involved in aerosol forcing and  
 2380 satellite and other observations.

2381  
 2382 To calculate the forcing time series and its uncertainty, individual ERF time series for  $\text{CO}_2$ , other  
 2383 GHGs, stratospheric ozone, tropospheric ozone, land-use surface albedo, black carbon on snow,  
 2384 stratospheric water vapor, contrails, solar and stratospheric volcanic aerosols are combined using  
 2385 Monte Carlo draws, assuming each time series has constant fractional uncertainty computed from  
 2386 the best estimate and the 5% to 95% range of the individual ERFs. These fractional uncertainties  
 2387 were based on the 1750–2011 ERF uncertainties from Myhre et al. (2013). Since historical  $\text{CO}_2$   
 2388 concentrations are accurately known, the uncertainty in  $\text{CO}_2$  ERF is assumed proportional to that  
 2389 in  $\Delta F_{2\times\text{CO}_2}$ . For terms other than aerosol, individual half-Gaussian PDFs are used for lower and  
 2390 upper bounds (Forster 2016; Myhre et al., 2013, 2015). For the total aerosol forcing including  
 2391 aerosol cloud interaction, samples from the unconstrained PDF of Bellouin et al. (2020) are scaled  
 2392 by a factor which reproduces the ranges of their PDF when applied to their forcing period  
 2393 (1850/2005–2015). The resulting PDF for  $\Delta F$  has a long tail towards smaller values because of the  
 2394 aerosol component (Figure 10 ), with a median of  $1.83 \text{ Wm}^{-2}$  and a 5-95% range of  $(-0.03,$   
 2395  $2.71) \text{ W m}^{-2}$ . Table 4 details the ERF best estimates used for the individual components and  
 2396 periods. The PDF of  $\Delta F_{2\times\text{CO}_2}$  is given in section 3.2.1 (see Table 1).

2397  
 2398 Results shown for comparison in Tables 4 and 5 also employ an aerosol estimate based on  
 2399 AR5 data (Boucher et al., 2013) which did not explicitly include energy budget studies, but did rely  
 2400 on expert judgement based on selected GCM results and satellite analyses. Figure 10  
 2401 compares both estimates for the Baseline period used here. The increased uncertainty range in  
 2402 Bellouin et al. (2020) compared to AR5 comes from assessing an increased number of aerosol-  
 2403 cloud-interaction processes, less confidence in the satellite-based estimates of aerosol forcing and  
 2404 different choices in expert judgement. The orange line in Figure 10 is the posterior of  $\Delta F$  that  
 2405 has been computed from the overall assessment of  $S$  in section 7 of the manuscript. In comparison  
 2406 to the prior PDFs, this is much more tightly constrained to positive forcing, ruling out a strongly  
 2407 negative aerosol ERF. This means that, in our analysis, it is more  $S$  that is providing a constraint of  
 2408 forcing over the historical period than vice versa (see Bellouin et al., 2020 and section 7).

#### 2409 4.1.2 Computing the likelihood

2410 The observed warming, increase in ocean heat uptake, and overall positive radiative forcing  
 2411 change constitute evidence for  $S_{\text{hist}}$  of above zero. To inform a PDF of  $S_{\text{hist}}$  we need the likelihood  
 2412  $P(E_{\text{hist}}/S_{\text{hist}}, \Delta N, \Delta F, \Delta F_{2\times\text{CO}_2})$ , which quantifies how likely it is that such evidence  $E_{\text{hist}}$  would be  
 2413 observed given a putative value of  $S_{\text{hist}}$  (see section 2.3). To obtain this we rearrange the energy  
 2414 balance (eq. 19 ) so that a forward model (cf. eq. 3) arises for the predicted temperature  
 2415 response  $\Delta T$  from each combination of inputs  $\Delta F$ ,  $\Delta N$ ,  $\Delta F_{2\times\text{CO}_2}$ , and  $S_{\text{hist}}$ :

$$2416 \Delta T = S_{\text{hist}} (\Delta F - \Delta N) / \Delta F_{2\times\text{CO}_2}, \quad (20)$$

2417  
 2418 where  $\Delta F$ ,  $\Delta N$ , and  $\Delta F_{2\times\text{CO}_2}$ , are random variables having specified prior distributions (i.e.,  
 2419

2420 uncertainties) which we randomly sample, hence generating a sample of possible  $\Delta T$  values, for  
 2421 any given  $S_{\text{hist}}$ . In doing this, to allow for the correlation between the CO<sub>2</sub>-forced part of  $\Delta F$  and  
 2422  $\Delta F_{2\times\text{CO}_2}$  (Otto et al., 2013; Lewis and Curry, 2015), we decompose  $\Delta F$  into its CO<sub>2</sub> and non-CO<sub>2</sub>  
 2423 constituent time series, and sample the latter independently of  $\Delta F_{2\times\text{CO}_2}$  before recombining to  
 2424 obtain the sample  $\Delta F$ . We assume that the (prior) PDFs of  $\Delta F$  and  $\Delta N$  are uncorrelated  
 2425 (independent). Note that  $\Delta T$  is not the observed warming, but the expected warming based on the  
 2426 other information, given  $S_{\text{hist}}$ . The difference between  $\Delta T$  and the best-estimate observation,  $\Delta T_{\text{obs}}$ ,  
 2427 equals the sum of the observational error and unforced variation of global-mean surface  
 2428 temperature, which has a Gaussian prior distribution with standard deviation  $\sigma_e$ . Hence the  
 2429 likelihood of the observed warming for any particular sampled combination of ( $\Delta F$ ,  $\Delta N$ , and  $\Delta F_{2\times\text{CO}_2}$ )  
 2430 is a Gaussian of width  $\sigma_e$  evaluated at  $\Delta T_{\text{obs}} - \Delta T$ , and the overall or “marginal” likelihood of the  
 2431 evidence given  $S_{\text{hist}}$  is found by averaging over the sample (see section 2.4.2). This analysis  
 2432 assumes that observational errors plus internal variability of  $\Delta N$  and  $\Delta T$  are independent. While it is  
 2433 possible there may be some correlation in geographic sampling errors, we expect any added  
 2434 uncertainty due to this to be swamped by other errors discussed below<sup>1</sup>.

2436 Figure 11 a shows the resulting likelihood for  $S_{\text{hist}}$ , with the maximum likelihood  $S_{\text{hist}} = 2.5$  K. If  
 2437 combined with a broad, uniform prior on  $S_{\text{hist}} \sim U(0,20)$  as common in published studies, this  
 2438 likelihood produces a posterior PDF for  $S_{\text{hist}}$  with a 5-95% range of 2.0-16.1 K and a median of 4.3  
 2439 K. These values of  $S_{\text{hist}}$  are higher than reported in recent publications (e.g., Forster, 2016; Lewis  
 2440 and Curry, 2018; Table 5 ) for two reasons. First, we are using updated values of  $\Delta T$ ,  $\Delta F$ , and  
 2441  $\Delta N$ . Second, this Bayesian PDF for  $S_{\text{hist}}$  is slightly different to the non-Bayesian distribution that  
 2442 would be obtained by substituting those of  $\Delta T$ ,  $\Delta F$ ,  $\Delta N$  and  $\Delta F_{2\times\text{CO}_2}$  directly into eq. (19) (5-95%  
 2443 range of 1.9–14.4 K and a median of 3.1 K; Table 5 and the green curve in Fig. 11 (b)).

2445 The primary contributor to uncertainty in  $S_{\text{hist}}$  is our limited knowledge of the historical forcing  
 2446 associated with anthropogenic, tropospheric aerosols (Figure 11 a). Aerosol forcing is important  
 2447 in determining the left-hand tail of the  $S_{\text{hist}}$  estimates: the lowest estimates of  $S_{\text{hist}}$  result when  
 2448 aerosol forcing is estimated to be small or positive. If aerosol forcing were around zero,  $S_{\text{hist}}$  could  
 2449 be as low as 1.2 K. The possibility of net positive aerosol forcing is also considered to be small  
 2450 based on process-based (thus, independent of energy balance models) estimates of aerosol  
 2451 effects (Bellouin et al., 2020). On the other hand, as we cannot rule out an aerosol forcing more  
 2452 negative than  $-2 \text{ W m}^{-2}$ , relatively high values of  $S_{\text{hist}}$  cannot be ruled out either.

2454 Secondary contributors to uncertainty in  $S_{\text{hist}}$  are the global warming trend and energy imbalance.  
 2455 Sensitivity tests are shown in Table 5 assessing the impact of (i) using a different aerosol  
 2456 forcing estimate, (ii) using a different base period (1850-1900 rather than 1861-1880), and (iii)  
 2457 using a global temperature estimate that is a blend of sea surface temperature over oceans and  
 2458 surface air temperature over land rather than being adjusted to produce a global surface air  
 2459 temperature product (SAT). These secondary contributors produce ~10% or smaller changes to  
 2460 central estimates of  $S_{\text{hist}}$ . Our main analysis in Table 5 uses Cowtan and Way SAT-derived  
 2461 temperatures from 1861-1880. While the present-day energy imbalance is well constrained by  
 2462 ocean temperature observations, the energy imbalance prior to about 2002 is uncertain, and we  
 2463 must rely entirely on models to estimate energy imbalance prior to about 1950. A sensitivity test of  
 2464 eliminating nearly all uncertainty in  $\Delta T$  and  $\Delta N$  (Fig. 11 a) demonstrates that the uncertainties in  
 2465 these values contribute little to the overall uncertainty in  $S_{\text{hist}}$ .

<sup>1</sup> Our calculations do not account for a small correlation between  $\Delta N$  and  $\Delta T$  (mean  $r^2$  of ~0.1) in the control simulations, which would have a negligible impact on the results.

### 2466 4.1.3 Consistency with estimates based on other forward models

2467 The energy budget approach used above facilitates comparison with several previous estimates.  
2468 However, it does not make full use of the observational record. In particular, by using only global  
2469 mean quantities diagnosed as differences between the two periods over a century apart, it does  
2470 not make use of any spatial or temporal information within the historical climate record. Temporal  
2471 information may be particularly useful to reliably account for the effect of volcanic forcing, which  
2472 can cause long-term change (e.g., Broennimann et al., 2019) including in the ocean (Gregory et  
2473 al., 2013; note that as 4.1.2 uses model-based estimates of ocean  $\Delta N$  to 1950 prior to  
2474 observations being available, this effect is negligible here). It can also make use of the difference  
2475 in time evolution of greenhouse gases versus aerosols after the 1980s, which can help disentangle  
2476 their effects (e.g., Undorf et al., 2018 and references therein). We ask in the present section: do  
2477 estimates that use both the spatial and temporal history of anthropogenic and naturally forced  
2478 warming further constrain  $S$ ? In other words, would we get different or stronger constraints if we  
2479 made use of that additional information?

2480  
2481 We address this question by first comparing the above results to an estimate based on the portion  
2482 of the observed surface and ocean warming that has been attributed to increasing greenhouse  
2483 gases (Tokarska et al., 2020a):  $\Delta T_{ghg}$ ,  $\Delta F_{ghg}$ , and  $\Delta N_{ghg}$ . Attribution makes use of the time-space  
2484 pattern of warming to disentangle the effects of other forcings, particularly aerosols, from those of  
2485 greenhouse gases and then applies the same energy budget equations (20) as above, but uses  
2486 attributed warming and greenhouse-gas-only forcing changes. This sharply reduces forcing  
2487 uncertainty, but increases uncertainty in the warming in the ocean and atmosphere, as there is  
2488 uncertainty in the amount of warming that can be attributed to greenhouse gases (see Bindoff et  
2489 al., 2013 for an assessment of attributed warming). Note that the analysis ends in 2012 due to the  
2490 availability of single-forcing simulations. Note also that it neglects changes in  $\Delta N$  other than ocean  
2491 warming, which are estimated to be small above. The results, shown in Figure 12, illustrate that  
2492 the use of the time-space pattern from observations in deriving attributed inputs to equation (20)  
2493 reduces uncertainty by effectively down-weighting very strong aerosol forcing as less consistent  
2494 with observations. Note that PDFs arising from this approach, using a flat prior in  $S_{\text{hist}}$ , yield  $S_{\text{hist}}$  of  
2495 1.3 to 3.1 K (5% to 95% interval with the most likely value at 2 K, and median 2.1 K).  
2496 Some studies have chosen to double the noise variance to address uncertainty in the pattern of  
2497 warming (e.g., Schurer et al., 2018) which would widen our results if done here (dotted lines in the  
2498 figure). In contrast, direct sampling of the distribution (dashes) rather than using a flat prior in  $S$   
2499 has a small influence on the PDF.

2500  
2501 As an alternative to the energy-budget approach, where  $S_{\text{hist}}$  is diagnosed from long-term changes  
2502 in Earth's energy budget discussed in section 4.1.2 and above for a greenhouse-gas-only energy  
2503 budget, several groups have employed a framework in which  $S_{\text{hist}}$  (or a feedback parameter  $\lambda$ ,  
2504 which is the inverse of  $S_{\text{hist}}$ ) is only one of multiple parameters of a simple dynamical model  
2505 simulating multiple physical processes. These dynamical models exploit differences in the spatio-  
2506 temporal responses to different forcings and are particularly effective in distinguishing between the  
2507 responses to abrupt forcings like volcanic eruptions and slower-varying forcings like greenhouse  
2508 gases. Generally, approaches use Bayesian priors and multiple free parameters (variables)  
2509 including climate sensitivity, aerosol forcing, and ocean effective diffusivity or a similar quantity. For  
2510 a given set of these variables, the dynamical model is integrated forward, and the likelihood is  
2511 computed by comparing observations to the full spatio-temporal model output. Posterior estimates  
2512 of  $S_{\text{hist}}$  arise from updating prior information on  $S_{\text{hist}}$ , aerosol forcing, and rate of ocean heat uptake,  
2513 using the dynamical model and observations; and then integrating out the latter two variables

2514 (Forest et al., 2002; Knutti et al., 2002; Frame et al., 2005). Many published estimates are  
2515 available (e.g., Andronova and Schlesinger, 2001; Forest et al., 2002; Lewis, 2015; Libardoni and  
2516 Forest, 2012; Aldrin et al., 2012; Skeie et al., 2018; Johansson et al., 2015; see Knutti et al., 2017  
2517 for references and details). Estimates will be the more powerful and reliable, the more data they  
2518 use up to the present period, the more effectively they use time-space patterns to distinguish  
2519 between causes of change, and the more state-of-the-art the aerosol forcing and climate models.  
2520 Note that posterior ranges of  $S_{\text{hist}}$  are sensitive to the choices of dynamical model and  
2521 observational dataset, suggesting that the complex spatio-temporal likelihoods employed with  
2522 these models can amplify both model structural differences (Annan, 2015; Bodman and Jones,  
2523 2016) and observational errors (Libardoni and Forest, 2011). Furthermore, the ranges are sensitive  
2524 to the choice of prior distributions (see e.g., Frame et al., 2005; Bodman and Jones, 2016; Lewis,  
2525 2014; Knutti et al., 2017; see also sections 2.4.4, 7.2 r). Figure 12 shows (for illustration  
2526 only) the results of two approaches when using a uniform prior in  $S_{\text{hist}}$ , which yields an estimate of  
2527 what a likelihood function against  $S$  would look like for comparison to the result of section 4.1.1.  
2528 Both estimates shown (Skeie et al., 2018, and Johansson et al., 2015) use a full Bayesian  
2529 treatment . These studies analyze similar observed periods (1880-2011 for Johansson; 1850-  
2530 2014 for Skeie et al., 2018) but use slightly different datasets for surface temperature and ocean  
2531 heat content and employ different time-dependent dynamical models, with separate  
2532 representations for land and ocean in Johansson (2015) and separate representations for northern  
2533 and southern hemisphere in Skeie et al. (2018). They also use different priors for model  
2534 parameters other than  $S_{\text{hist}}$ , differ in their treatment of volcanism and total forcing uncertainty, and  
2535 use different estimates of natural variability (e.g., the Johannsen et al. estimate widens if not using  
2536 ENSO as a covariate).

2537  
2538 These choices translate to large differences in estimates of  $S_{\text{hist}}$ . Skeie et al. (2018) report a 90%  
2539 interval of 1.2-3.1 K, while Johansson et al. (2015) estimates a 5-95% range of 2.0 to 3.2 K (for a  
2540 comparison of all available estimates to date, see Knutti et al., 2017). We attempted to encompass  
2541 both results into a synthetic PDF based on an inverse Gaussian (not shown), which maintained a  
2542 thicker tail on the right-hand side from both estimates by matching the 95th percentile, but  
2543 encompassed the Skeie et al. lower 5% tail and widened this tail (making the 10-90% range fit the  
2544 5-95% range) to account for overall structural uncertainties. The resulting PDF was very close to  
2545 the greenhouse-gas-attributed case (red curve) for doubled variance shown in Figure 11 .  
2546

2547 We emphasize that neither the global energy budget approach (section 4.1.2) nor fitted dynamical  
2548 models provide a purely observational constraint on  $S_{\text{hist}}$ . The estimates of  $\Delta T$ ,  $\Delta F$ ,  $\Delta N$ , and  $\Delta F_{2xCO_2}$   
2549 used are necessarily based on a combination of observational data with multiple models. Climate  
2550 model data are employed to estimate global-mean, near-surface air temperature change, to infer  
2551 missing values, or the effects of blending (Cowtan et al., 2015; Richardson et al., 2016). ERF time  
2552 series depend on radiative transfer models and model-estimated aerosol effects and climatological  
2553 atmospheric structure. And though observations of ocean warming over recent decades provide  
2554 increasingly precise estimates of the modern global energy imbalance (Johnson et al., 2016;  
2555 Trenberth et al., 2016), climate models are necessary to evaluate the global energy imbalance  
2556 during the pre-industrial period against which historical warming is compared (e.g., Lewis and  
2557 Curry, 2015) as well as its internal variability.

2558  
2559 Moreover, even the energy budget equation (section 4.1) is a simplified model (Hegerl and Zwiers,  
2560 2011). There are several notable assumptions inherent in this model (see section 2.2). For  
2561 instance, it assumes that the global temperature response to an equivalent magnitude of forcing  
2562 associated with different radiative forcing agents or global ocean heat uptake will be the same.



2563 Equation (19) also assumes that global radiative response to warming is exactly proportional to  
2564 global-mean temperature change, and that the radiative feedbacks governing radiative response  
2565 do not vary in time or state. As the radiative response to warming varies within comprehensive  
2566 global climate models (e.g., Winton et al., 2010; Armour et al., 2013; Rose et al., 2014; Shindell  
2567 2014; Andrews et al., 2015; Marvel et al., 2015; Proistosescu et al., 2017; Armour 2017; Ceppi and  
2568 Gregory 2017; Marvel et al., 2018; Andrews et al., 2018; Dong et al., 2020) energy-balance models  
2569 could be developed that account for such variation (e.g., Ceppi and Gregory, 2019). In the next  
2570 section, we explore these limitations and consider the extent to which estimates of  $S_{\text{hist}}$  from the  
2571 historical record constrain the effective climate sensitivity  $S$  targeted in this assessment.

2572  
2573 The rate of warming since only the 1970s or 1980s can also be exploited as an emergent  
2574 constraint on TCR and on climate sensitivity (when accounting for the nonlinearity in the response  
2575 between the present day and equilibrium), as aerosol forcing changes are thought to be relatively  
2576 small over this period in the global mean (Jiménez-de-la-Cuesta and Mauritsen, 2019; Tokarska et  
2577 al., 2020b). The more recent CMIP6 models have a wider range of climate sensitivity than CMIP5,  
2578 and many exhibit a strong warming since the 1970s (Forster et al., 2019), allowing for a relatively  
2579 strong emergent constraint on TCR (Winton et al, 2020; Nijssse et al., 2020; Tokarska et al.,  
2580 2020b). These estimates are susceptible to potentially large and unaccounted for uncertainties in  
2581 the pattern effect which make it challenging to constrain  $S$  from such methods (Jiménez-de-la-  
2582 Cuesta and Mauritsen, 2019). They also likely underestimate the role of aerosol radiative forcing  
2583 and its uncertainty as they assume the models' small aerosol forcing change since 1970 is correct,  
2584 whereas aerosol forcing evolution might be more complicated (Ragayre et al., 2015).

2585  
2586 Overall, using the time-space information of past warming, either by fitting a simple model or  
2587 estimating the greenhouse gas contribution only to recent observed changes, tends to reduce the  
2588 upper tail of  $S_{\text{hist}}$  while maintaining the lower (compare Figure 11 and 12). This suggests  
2589 that some of the stronger aerosol forcing values included in the recent, wider estimate of forcing  
2590 uncertainty used in section 4.2 are not readily compatible with historical observations, although  
2591 uncertainty in these 'top-down' estimates of aerosol are substantial, and the time evolution of the  
2592 forcing rather than its magnitude can also contribute to any poor fit seen with historical  
2593 observations. Nevertheless, we carry forward the estimate of  $S_{\text{hist}}$  that is based on the overall  
2594 energy budget (section 4.1.2., Figure 11). We do so because it is the most up-to-date estimate,  
2595 and requires the least assumptions such as in the time-space pattern of aerosol forcing, which is  
2596 quite uncertain (Schurer et al., 2018).

## 2597 **4.2 Transitioning from $S_{\text{hist}}$ to $S$**

2598  
2599 Given constraints on  $S_{\text{hist}}$  from the historical climate record, what can be said about the effective  
2600 sensitivity  $S$  as defined in section 2.1? If radiative feedbacks near equilibrium under  $\text{CO}_2$  forcing  
2601 were identical to the responses governing historical warming—in other words if there were a  
2602 unique, linear relationship between  $\Delta N - \Delta F$  and  $\Delta T$ —then  $S$  would be equivalent to  $S_{\text{hist}}$ . However,  
2603 there is growing evidence that this relationship has not been constant in time and that the  
2604 sensitivity  $S_{\text{hist}}$  inferred over the historical period may underestimate  $S$ , due to complications noted  
2605 at the end of section 2.2.

2606  
2607 Recognition of this problem began with model studies, but its key components have since been  
2608 identified in observations as well. Many studies spanning multiple generations of climate models  
2609 have found a strong tendency for radiative feedbacks to become less negative—an increase in

2610 climate sensitivity—as equilibrium is approached (Murphy, 1995; Senior and Mitchell, 2000;  
2611 Williams et al., 2008; Winton et al., 2010; Armour et al., 2013; Geoffroy et al., 2013; Li et al., 2013;  
2612 Rose et al., 2014; Andrews et al., 2015; Marvel et al., 2015; Gregory and Andrews, 2016; Zhou et  
2613 al., 2016; Knutti and Rugenstein, 2015; Rugenstein et al., 2016; Armour, 2017; Proistosescu et al.,  
2614 2017; Ceppi and Gregory, 2017; Lewis and Curry, 2018). This behavior arises from the fact that  
2615 the global radiative response  $\Delta N$  to surface warming depends on the *spatial pattern* of that  
2616 warming (Winton et al., 2010; Armour et al., 2013; Andrews et al., 2015; Paynter and Frölicher  
2617 2015; Gregory and Andrews, 2016; Andrews and Webb, 2018; Zhou et al., 2017; Dong et al.,  
2618 2019; Marvel et al., 2018; Andrews et al., 2018). The spatial pattern of warming can evolve for a  
2619 number of reasons including the different timescales of ocean adjustment at different geographic  
2620 locations (e.g., Stouffer, 2004; Marshall et al., 2015; Rugenstein et al., 2016b), an evolving  
2621 importance of different radiative forcing agents (Hansen et al., 2004; Shindell, 2014; Marvel et al.,  
2622 2015), and internal climate variability (note that while the estimates of  $S_{\text{hist}}$  discussed above include  
2623 the effect of internal variability on  $\Delta T$  itself, they do not include its other impacts on the radiation  
2624 balance  $\Delta N$ ). The resulting changes in apparent feedback strength as spatial patterns of warming  
2625 evolve have therefore been termed “pattern effects” (Stevens et al., 2016), distinguishing them  
2626 from a feedback dependence on the magnitude of global-mean warming (e.g., Caballero and  
2627 Huber, 2013; Meraner et al., 2013; Bloch-Johnson et al., 2015; see section 5.1.3).

2629 New studies have clarified how pattern effects are likely to work. Figure 13 illustrates the key  
2630 components of how temperature patterns are expected to affect  $\Delta N$ . Warming in the west Pacific  
2631 warm pool, a region of deep ascent in the troposphere, warms the troposphere and increases  
2632 tropospheric stability throughout the tropics. In turn, this gives rise to enhanced radiation to space  
2633 and enhanced low-cloud cover (e.g., Wood and Bretherton, 2006; Zhou et al., 2016; Andrews and  
2634 Webb, 2018; Ceppi and Gregory, 2017; Dong et al., 2019). In contrast, warming in the east Pacific,  
2635 a region of overall descent, is trapped in the lower troposphere, decreasing tropospheric stability  
2636 and leading to a reduction in low cloud cover (see section 3.3.2). The result is that warming in the  
2637 west Pacific produces negative cloud and lapse-rate feedback responses while warming in the  
2638 east Pacific produces more positive ones (Fig. 13 c). Warming at high latitudes produces a  
2639 muted radiative response associated with positive lapse-rate and sea-ice feedbacks (Armour et al.,  
2640 2013; Po-Chedley et al., 2018; Dong et al., 2019) as well as through an impact on cloud cover  
2641 through changes in tropospheric stability (Senior and Mitchell, 2000; Winton et al., 2010; Rose et  
2642 al., 2014; Rose and Rayborn, 2016; Trossman et al., 2016).

2644 The impact of varying tropical sea surface temperature patterns on cloud cover on decadal to  
2645 centennial time scales, which is thought to dominate the pattern effects in models (Andrews et al.,  
2646 2015; Zhou et al., 2017; Dong et al., 2019), has been seen in satellite observations as well.  
2647 Specifically the observational studies of Zhou et al. (2016), Loeb et al. (2018), Ceppi and Gregory  
2648 (2017), Fueglistaler (2019), and Loeb et al. (2020) find evidence for a pattern effect in the satellite  
2649 records of cloud cover and TOA radiation as well as in atmospheric reanalysis fields of  
2650 tropospheric stability. Importantly, GCMs appear to be able to capture the essential physical  
2651 mechanisms linking sea surface temperature patterns to radiative response (Loeb et al., 2020),  
2652 providing confidence in the theory behind the pattern effect and the use of models to estimate how  
2653 radiative feedbacks may change with evolving warming patterns (section 4.2.1).

2655 The dependence of  $\Delta N$  on warming pattern implies that  $S_{\text{hist}}$  will provide an accurate estimate of  $S$   
2656 only if the pattern of long-term forced warming is similar to the observed pattern of warming over  
2657 the historical record. However, the projected pattern of long-term warming in response to  $\text{CO}_2$   
2658 forcing (Fig. 13 b) is strikingly different from the pattern of observed warming over the historical

2659 period (Fig. 13 a). While the predicted forced pattern is smooth, the observed pattern is highly  
2660 heterogeneous with little long-term warming in the east Pacific and Southern Ocean. This indicates  
2661 that if our understanding of cloud responses and the forced warming patterns is correct, the  
2662 historical record includes cloud responses that have damped warming, but which will not persist in  
2663 the long term. While the observed pattern is subject to uncertainties especially earlier in the record,  
2664 the pattern since 1900 is robust across several station-based datasets (Solomon and Newman,  
2665 2012), and its key features are supported by sea-level pressure trends (L'Heureux et al., 2013) and  
2666 are consistent with trends reported for more recent periods in Pacific trade winds (England et al.,  
2667 2014) and sea level (Rhein et al., 2013; White et al., 2014).

2668  
2669 There are likely multiple reasons for the heterogeneous historical warming. As discussed above,  
2670 comprehensive GCMs predict some robust changes in the pattern of warming as the climate  
2671 equilibrates to an imposed greenhouse gas forcing. In particular, warming tends to be delayed  
2672 within the eastern equatorial Pacific and Southern Ocean, which are regions of ocean upwelling  
2673 (e.g., Clement et al., 1996; Marshall et al., 2015; Armour et al., 2016). Yet the GCMs predict that  
2674 warming in those regions will eventually become amplified relative to their surroundings (e.g., Li et  
2675 al., 2013), resulting in more positive climate feedbacks and an increase in climate sensitivity as  
2676 equilibrium is approached (Winton et al., 2010; Andrews et al., 2015; Geoffroy et al., 2013;  
2677 Rugenstein et al., 2016; Armour, 2017; Proistosescu et al., 2017). Indeed, enhanced warming  
2678 within these regions can be seen in the warming predicted by CMIP5 models over the 150 years  
2679 following an abrupt CO<sub>2</sub> quadrupling (Fig. 13 b)—the period corresponding to our climate  
2680 sensitivity metric  $S$  within the models. Enhanced temperature changes within these regions are  
2681 also supported by proxy reconstructions of past climate states (Masson-Delmotte et al., 2013;  
2682 Tierney et al., 2019, 2020). The observed warming pattern (Fig. 13 a) is atypical compared to  
2683 historical simulations of climate models. Some of the heterogeneity in early 20th Century SST  
2684 trends may reflect unaccounted-for offsets among groups of measurements (Chan et al., 2019),  
2685 but there remain discrepancies between modeled and observed warming over this period (Hegerl  
2686 et al., 2018). It is unclear if these reflect stronger internal variability than simulated in some GCMs,  
2687 observational error, or a combination of both. GCMs are also not generally able to capture the far-  
2688 better observed pattern of SST trends since ~1980, particularly in the tropical Pacific Ocean (Zhou  
2689 et al., 2016) and Southern Ocean (Kostov et al., 2018).

2690  
2691 The observed pattern of SST changes since ~1980 resembles internal variability such as the  
2692 negative phases of the Interdecadal Pacific Oscillation (Meehl et al., 2016; Mauritsen, 2016) and  
2693 Southern Annular Mode (Kostov et al., 2018), and recently each seems to have begun reversing  
2694 (e.g., Stuecker et al., al. 2017; Loeb et al., 2018). This suggests a likely contributing role from  
2695 unforced variability. It is possible the observed warming pattern also contains a signature of  
2696 external forcing, such as by stratospheric ozone changes (Marshall et al., 2014), aerosols or  
2697 volcanic eruptions (Schmidt et al., 2014; Santer et al., 2015; Takahashi and Watanabe, 2016), or  
2698 that it constitutes a forced response not captured by models (e.g. McGregor et al., 2018; Kohyama  
2699 et al., 2017; Seager et al., 2019; see discussion in section 5).

2700  
2701 Regardless of the cause, the relative lack of observed warming within these key geographic  
2702 regions implies that radiative feedbacks will become less negative in the future *if* the long-term  
2703 warming pattern becomes more similar to that suggested by GCM simulations, paleo proxies and  
2704 theory, suggesting that  $S$  may be larger than that implied by  $S_{\text{hist}}$ .

## 4.2.1 Quantifying the historical pattern effect

The implication from current evidence outlined above is that the long-term feedback under CO<sub>2</sub> forcing,  $\lambda$ , will be less negative than the apparent historical feedback,  $\lambda_{hist}$ . Here we use CMIP5 and CMIP6 GCMs to quantify this feedback change, denoted  $\Delta\lambda = \lambda - \lambda_{hist}$ . Rearranging eq. (6) following eq. (20), we write

$$\Delta T = -(\Delta F - \Delta N) / (\lambda - \Delta\lambda) \quad (21)$$

allows us to evaluate the likelihood function of  $\lambda$  and in turn of our target climate sensitivity according to  $S = -\Delta F_{2xCO_2} / \lambda$  (see section 2.3).

Climate models generally suggest that feedbacks will become less negative in the future ( $\Delta\lambda > 0$ ) as the spatial pattern of warming evolves, but because models do not fully reproduce observed patterns, there are uncertainties in how best to quantify this. Armour (2017) and Lewis & Curry (2018) considered changes in radiative feedbacks in CMIP5 model simulations with gradually increasing CO<sub>2</sub> at a rate of 1 percent per year (“1pctCO<sub>2</sub>”) (Gregory et al., 2015; Armour, 2017), taking year 100 as an analog for historical warming. Comparing  $\lambda_{hist}$  with each model’s effective feedback  $\lambda$  (estimated as  $\lambda = -\Delta F_{2xCO_2} / S$  within simulations of abrupt CO<sub>2</sub> quadrupling abrupt4xCO<sub>2</sub>), they find that the majority of models show a less negative global radiative feedback under abrupt4xCO<sub>2</sub> than under 1pctCO<sub>2</sub>, with an average radiative feedback change of  $\Delta\lambda = +0.2 \text{ W m}^{-2} \text{ K}^{-1}$  (–0.1 to +0.6  $\text{W m}^{-2} \text{ K}^{-1}$  range across models) from Armour (2017) and  $\Delta\lambda = +0.1 \text{ W m}^{-2} \text{ K}^{-1}$  (–0.2 to +0.2  $\text{W m}^{-2} \text{ K}^{-1}$  range across models) from Lewis and Curry (2018). Note these values differ slightly from those in Armour (2017) and Lewis and Curry (2018) who estimated  $S$  based on a regression over years 21-150 following abrupt CO<sub>2</sub> quadrupling rather than years 1-150 as done here. Using the early portion of abrupt4xCO<sub>2</sub> simulations as an analogue for historical warming and following the methods of Lewis and Curry (2018), Dong et al. (2020) find an average radiative feedback change of  $\Delta\lambda = +0.1 \text{ W m}^{-2} \text{ K}^{-1}$  (–0.2 to +0.3  $\text{W m}^{-2} \text{ K}^{-1}$  range across models) for CMIP5 models and  $\Delta\lambda = +0.1 \text{ W m}^{-2} \text{ K}^{-1}$  (–0.1 to +0.3  $\text{W m}^{-2} \text{ K}^{-1}$  range across models) for CMIP6 models.

A limitation of using 1pctCO<sub>2</sub> and abrupt4xCO<sub>2</sub> simulations to estimate feedback changes is that they do not account for the influence of non-CO<sub>2</sub> forcing agents (in particular, aerosols which force the system very heterogeneously) and internal variability. Ideally, feedback changes could be quantified within historical forcing simulations, but this quantification has been made for only those few GCMs within which the historical radiative forcing has been quantified accurately enough for calculations of  $\lambda_{hist}$  to be performed. Using historical simulations of the latest Hadley Centre Global Environmental Model (HadGEM3-GC3.1-LL), Andrews et al., (2019) find an average radiative feedback change of  $\Delta\lambda = +0.2 \text{ W m}^{-2} \text{ K}^{-1}$  (–0.2 to +0.6  $\text{W m}^{-2} \text{ K}^{-1}$  range across four ensemble members). This value is on average larger than the  $\Delta\lambda = +0.04 \text{ W m}^{-2} \text{ K}^{-1}$  estimated using the early portion of the model’s abrupt4xCO<sub>2</sub> simulation (Dong et al., 2020), suggesting that the value of  $\Delta\lambda$  may depend on having a realistic representation of historical forcing and of volcanic forcing in particular (Gregory et al., 2019). However, there is substantial spread in the value of  $\Delta\lambda$  across ensemble members, consistent with the results of Dessler et al. (2018) who find that internal climate variability alone results in a  $0.5 \text{ W m}^{-2} \text{ K}^{-1}$  spread in  $\lambda_{hist}$ , and thus also in the value of  $\Delta\lambda$  across a 100-member, historical-simulation ensemble of the Max Planck Institute Earth System Model (MPI-ESM1.1). Altogether, these coupled model results suggest mean value of around  $\Delta\lambda = 0.2 \text{ W m}^{-2} \text{ K}^{-1} \pm 0.4 \text{ W m}^{-2} \text{ K}^{-1}$  (5-95% range). Assuming Gaussian uncertainties, eq. (21),

2753 along with historical estimates of  $\Delta T$ ,  $\Delta F$ ,  $\Delta N$ , results in a maximum likelihood for  $S = 2.9$  K (green  
2754 line in Fig. 14 , Table 6 ), somewhat higher than the equivalent value of 2.5 K for  $S_{\text{hist}}$   
2755 (black line in Fig. 11 a, Table 6 ).

2756  
2757 If models are to be a credible guide to the size of the pattern effect, they must accurately capture  
2758 the relative patterns of historical and long-term temperature change. However, historical and  
2759 1pctCO2 simulations of coupled models generally produce patterns of warming that more closely  
2760 resemble that of their abrupt4xCO2 simulations rather than that of observed warming (Fig. 13 ;  
2761 Seager et al., 2019), suggesting that these simulations may underestimate the pattern effect  
2762 (Marvel et al., 2018; Andrews et al., 2018).

2763  
2764 An alternative approach is to estimate the pattern effect on the basis of differences between the  
2765 observed  $\Delta\text{SST}$  pattern and the anticipated long-term one. This method does not rely on model  
2766 calculations of transient change, but does rely on an accurate long-term  $\Delta\text{SST}$  pattern. To  
2767 implement this method we use atmosphere-only simulations wherein observed SSTs and sea-ice  
2768 concentrations are prescribed as boundary conditions (Gregory and Andrews, 2016; Zhou et al.,  
2769 2016; Silvers et al., 2017; Andrews et al., 2018; Dong et al., 2019). All other boundary conditions  
2770 (greenhouse gases, aerosols, etc.) are held fixed in time such that the SST and sea-ice impact on  
2771 the radiation balance (the feedback) can be estimated by linear regression. These atmosphere-  
2772 only model simulations exhibit values of  $S_{\text{hist}}$  that range from 1.6-2.1 K, in good agreement with that  
2773 derived from global energy budget constraints (section 4.1.2) and unanimously lower than values  
2774 of  $S$  found in abrupt4xCO2 simulations using the same models (2.4 to 4.6 K) (Andrews et al.,  
2775 2018). Andrews et al. (2018) collect all existing such model runs (from six different models, albeit  
2776 only from four modeling centers), and find an ensemble-mean value of  $\Delta\lambda = +0.6 \text{ W m}^{-2} \text{ K}^{-1}$  (+0.3  
2777  $\text{W m}^{-2} \text{ K}^{-1}$  to +1.0  $\text{W m}^{-2} \text{ K}^{-1}$  range across models). Similar values are found if the equilibrium  
2778 feedback is estimated as  $\lambda = -\Delta F_{2\times\text{CO}_2}/S$  rather than from the regression over years 1-150  
2779 following abrupt CO<sub>2</sub> quadrupling as in Andrews et al. (2018).

2780  
2781 We prefer this approach for estimating the pattern effect because it is derived using observed  
2782 SSTs and is thus not biased by errors in historical SSTs simulated by coupled models. However,  
2783 this estimate still hinges on several key considerations. The first is that it relies on the accuracy of  
2784 the observed SST and sea-ice changes. Using alternative SST datasets, Andrews et al. (2018)  
2785 found little change in the value of  $\Delta\lambda$  within two models (HadGEM3 and HadAM3). The sensitivity  
2786 of results to the choice of dataset represents a source of uncertainty in the quantification of  $\Delta\lambda$   
2787 using atmosphere-only GCMs that has not been fully explored. The second consideration is that it  
2788 relies on the abrupt4xCO2 pattern of warming simulated by coupled models (Fig. 13 b) being an  
2789 accurate representation of long-term response to CO<sub>2</sub> forcing. If the long-term warming pattern  
2790 were to resemble that of observed historical warming, this would imply a value of  $S$  that is closer to  
2791 our assessed value of  $S_{\text{hist}}$ . The inability of coupled models to capture the observed pattern of  
2792 warming in the tropical Pacific (e.g., Seager et al., 2019) and Southern Ocean (e.g., Armour et al.,  
2793 2016) may call into question their ability to accurately simulate the long-term pattern of warming.  
2794 However, a range of observational evidence from paleoclimate proxies and theory suggest that  
2795 amplified warming in the southern high latitudes will indeed eventually emerge (Masson-Delmotte  
2796 et al., 2013) once the deep ocean waters that are upwelled to the Southern Ocean surface are  
2797 warmed, likely taking hundreds of years or more (Armour et al., 2016). Moreover, proxy data since  
2798 the Pliocene suggests that warming in the eastern tropical Pacific will eventually become amplified  
2799 relative to the west (Tierney et al., 2019, 2020) as the upwelled water stems mostly from mid-  
2800 latitudes (Fedorov et al., 2015). Moreover, as noted above, much current evidence points to the  
2801 observed pattern of warming being strongly influenced by internal variability and/or short-lived

2802 climate forcers. This suggests that the observed warming pattern is transient in nature. Thus we  
2803 assign a low probability that the forced pattern will strongly resemble the historically observed one.  
2804

2805 A third consideration is whether the models used here to quantify the pattern effect faithfully  
2806 represent the clouds and corresponding radiation response to these SST patterns. Comparison of  
2807 NCAR's CAM5 to observed low-cloud trends in the East Pacific revealed that the model may  
2808 underestimate the cloud increase (Zhou et al., 2016). Analysis of six CMIP6 models driven by  
2809 observed SST and sea-ice boundary conditions suggests that the models can generally replicate  
2810 top-of-atmosphere radiation changes observed by satellite over 2000–2018, but that the models  
2811 may underestimate the sensitivity of global radiation to SST changes and thus the magnitude of  $\Delta\lambda$   
2812 (Loeb et al., 2020). A final consideration is the extent to which the quantification depends on the  
2813 selection of models used. The six models used here (from Andrews et al., 2018) represent an  
2814 ensemble of opportunity, and it is unlikely that they capture all possible future feedback changes. A  
2815 broader analysis would be needed to draw conclusions as to whether the methods employed here  
2816 are biased.  
2817

2818 In light of these considerations, we choose for our main analysis  $\Delta\lambda = +0.5 \text{ W m}^{-2} \text{ K}^{-1}$  with  
2819 Gaussian uncertainty  $\pm 0.5 \text{ W m}^{-2} \text{ K}^{-1}$  (5-95% range). This range is informed by the Andrews et al.  
2820 (2018) estimate of the pattern effect based on observed SSTs but allows for a greater (though still  
2821 small) possibility that the pattern effect may be smaller than reported in that study. Using this mean  
2822 value of  $\Delta\lambda$  and uncertainty in eq. (21), along with historical estimates of  $\Delta T$ ,  $\Delta F$ ,  $\Delta N$ , results in  
2823 a maximum likelihood for  $S = 3.8 \text{ K}$ , substantially higher than that of  $S_{\text{hist}}$  derived in section 4.1.2 or  
2824 that of  $S$  derived from transient coupled models (Fig. 14, Table 6). Combining this likelihood  
2825 (black line in Fig. 14) with a broad uniform prior on  $S \sim U(0,20)$  yields a posterior with a 2.8 to 18.6  
2826 K 5-95% range (note that this large upper limit indicates that the data do not constrain  
2827 the upper limit of climate sensitivity beyond the prior).  
2828

2829 This estimate of the historical likelihood for  $S$  using a pattern effect based on observed SSTs  
2830 follows our preferred approach, and we carry this forward into section 7 to be combined with other  
2831 lines of evidence. However, we also consider the sensitivity of the results to a halving of the  
2832 uncertainty on our assessed value of  $\Delta\lambda$  (Fig. 14). This reduces the 5-95% range slightly when  
2833 combined with a  $S \sim U(0,20)$  prior slightly from 2.8-18.6 K to 2.9-18.5 K. These results suggest that  
2834 the historical record currently provides only weak constraints on  $S$ , and that improved  
2835 quantification of both the pattern effect and the historical aerosol forcing is necessary to rule out  
2836 high values of  $S$  in particular.  
2837

## 2838 4.3 Summary

2839  
2840 Because the climate sensitivity  $S$  would directly affect the magnitude of any radiatively-forced  
2841 climate change, the magnitudes of known changes can constrain  $S$  if enough is known about what  
2842 drove them. The best-observed example is the warming over the instrumental period. In this  
2843 section we assessed what this warming tells us about  $S$ . Over this period the greenhouse gas  
2844 forcings are known fairly accurately, while the largest uncertainties are the strength of non-GHG  
2845 forcings and the impact of non-equilibrium effects. These effects matter because the warming  
2846 period is not very long compared to time scales of natural variability and system response lags.  
2847

2848 The best-known non-equilibrium effect is the top-of-atmosphere (and surface) energy imbalance,

2849 which persists for decades to centuries after an applied forcing due to the long time required for  
2850 the oceans to fully equilibrate. This imbalance is reflected in changes in global ocean heat content,  
2851 which, along with the surface warming, is reasonably well measured in recent decades, albeit with  
2852 errors larger than sometimes appreciated.

2853  
2854 To quantify how consistent various climate sensitivities are with the evidence, following past  
2855 studies, we calculate a likelihood of the observed ocean heat content and surface temperature  
2856 changes as a function of  $S$ . This calculation employs a PDF of total radiative forcing, based on  
2857 direct observations and models of the various forcing agents and their radiative effects.

2858  
2859 A second non-equilibrium effect has recently come to the fore which significantly affects the  
2860 likelihood function, called here the historical “pattern effect.” Ocean surface warming in recent  
2861 decades has occurred in a much more heterogeneous geographic pattern than that predicted at  
2862 equilibrium under  $\text{CO}_2$  forcing. Model simulations and satellite observations now show that this  
2863 recent heterogeneity has driven net increases in low-cloud cover and global albedo, reducing the  
2864 warming relative to what it would have been with a smoother, equilibrium pattern of warming. If as  
2865 expected this heterogeneous pattern is temporary (either a transient or a natural fluctuation), the  
2866 implication is that  $S$  inferred from historical warming using straightforward assumptions or simple  
2867 models with constant  $S$ , which we have denoted  $S_{\text{hist}}$ , is less than the true  $S$ . The direction of this  
2868 bias is physically understood and we are confident about that, but its magnitude is highly uncertain  
2869 because we rely heavily on GCM simulations to quantify it. The development of observational  
2870 constraints on the magnitude of the pattern effect are critical to be able to better constrain the  
2871 likelihood of high values of  $S$  based on historical evidence.

2872  
2873 Taking all the above factors into account we find that given the historical evidence, the maximum-  
2874 likelihood value is  $S = 3.8 \text{ K}$ , but values between 1.9 and 20 K and above can still be considered  
2875 consistent with the evidence (likelihood  $> 0.2$ ). In particular the historical observed climate change  
2876 provides a strong constraint on the lower bound of  $S$ , effectively ruling out negative feedbacks, but  
2877 only a very weak constraint on the upper bound. This latter conclusion, which differs from many  
2878 previously published studies using the historical record, arises in part because the “pattern effect”  
2879 could potentially allow even high values of  $S$  to be reconcilable with only moderate historical  
2880 warming. The possibility of strong negative aerosol ERF also precludes setting a tight upper bound  
2881 on  $S$ . Indeed our high-likelihood range for  $S_{\text{hist}}$  (not accounting for the pattern effect) is consistent  
2882 with most of those previous studies if we use older forcing and warming estimates, so the increase  
2883 here is due to revised estimates rather than any difference in methodology. The Bellouin et al.  
2884 (2020) aerosol ERF used here allows more negative tails than some recent estimates, especially  
2885 those that implicitly match aerosol forcing to the observed warming. Previous studies that have not  
2886 accounted particularly for the pattern effect produced energy budget constraints on  $S$  that were  
2887 unjustifiably tight and too low.

2888  
2889 The historical warming does provide strong evidence against  $S$  of  $\sim 1.5 \text{ K}$  or less, because roughly  
2890 1 K of warming has already occurred, and this is likely all a forced signal (Allen et al, 2018; see  
2891 also Bindoff et al., 2013; Schurer et al., 2018); this realized warming is less than the equilibrium  
2892 warming, and from a forcing almost certainly less than  $\Delta F_{2\times\text{CO}_2}$ . Even assuming a very small  
2893 aerosol forcing, the lowest plausible observed warming (neglecting known negative biases), and  
2894 the highest plausible radiative imbalance during the base period, it seems nearly impossible to  
2895 assign non-negligible likelihoods to values of  $S_{\text{hist}}$  (let alone  $S$ ) less than 1.2 K. To reconcile the  
2896 evidence with an  $S$  below even 2 K under reasonable PDFs of observed warming and imbalance  
2897 would require either aerosol forcing to be near zero, or for aerosol forcing to be weak and the

2898 pattern effect to be weaker than expected.

2899

2900 Accordingly, the historical record offers potential to further narrow the  $S$  range at both ends with  
2901 further research progress. If weak aerosol forcings can be ruled out, for example, the constraint at  
2902 the low end could rise (this may also gradually happen with further warming, if it continues at the  
2903 pace of the last few years). If the limit of strongly negative aerosol forcing were constrained, this  
2904 would sharply reduce the upper tail as it would no longer allow very small net forcing which, in  
2905 combination with large warming, leads to high estimates. On the other hand, if further research can  
2906 limit the maximum size of the pattern effect on the historical radiative balance, this could permit the  
2907 record to bound the high end of  $S$ , especially if aerosol forcing uncertainty is reduced. Future  
2908 avenues of research employing decadal changes and regional patterns with emergent constraints  
2909 over the historical period may eventually be able to place a tighter constraint on  $S_{\text{hist}}$  that avoids  
2910 issues of circularity arguments with estimates of aerosol forcing, which combined with improved  
2911 quantification of the pattern effect, may lead to a tight bound on  $S$ .



## 5. Constraints from paleoclimate records

2915 Climate sensitivity estimates using paleoclimate information rely on a basic paradigm that there are  
 2916 times before the instrumental period for which we have a reasonable estimate of a climatic state. In  
 2917 particular, this concerns an estimate for global mean temperature that was sufficiently stable over  
 2918 centuries to millennia (i.e., in a quasi-equilibrium state), together with estimates of how forcings  
 2919 differed from the “pre-industrial” state. From these we can derive estimates of the overall sensitivity  
 2920 of the climate state to radiative forcings. This means that, in contrast to studies of historical  
 2921 constraints (section 4), paleoclimate studies do not consider disequilibrium in the planetary energy  
 2922 budget or ocean heat content and in principle we can use the energy balance equation (3).  
 2923 However, we must contend with not just changes in greenhouse gases, but also changes in land  
 2924 surface vegetation, ice (land and sea), topography, and even potentially continental shapes and  
 2925 position (Farnsworth et al., 2019) for deep time periods, as well as other forcing and climate  
 2926 uncertainties that arise from the more limited information available. This requires equation (3) to  
 2927 be modified with various additional terms (see also section 2.2). These terms will be discussed in  
 2928 more detail as they are introduced in the following subsections.

2930 To make climate sensitivity estimates from paleoclimate data compatible with the parameter  $S$   
 2931 targeted in this report (section 2.1), the influence of slow feedback processes needs to be explicitly  
 2932 resolved. Feedbacks resulting from the expansion and reduction of continental ice sheets are  
 2933 particularly important. The effects of vegetation and land-surface changes, and (partly vegetation-  
 2934 related) dust aerosol influences also need to be considered. While  $\text{CO}_2$  and  $\text{CH}_4$  concentrations  
 2935 can act as feedbacks to other climate changes as well as forcings on paleo time scales, care  
 2936 needs to be taken to account for this in estimates of  $S$ ; all that is available are total values for  $\text{CO}_2$   
 2937 and  $\text{CH}_4$  concentrations during the last 800,000 years (from ice cores), and only  $\text{CO}_2$  for older  
 2938 times. Furthermore, in reality feedback strength is not a constant parameter of the climate system;  
 2939 in particular, it may vary with the climate state and applied forcing, and this variation may be  
 2940 significant in the context of paleoclimate.

2942 We consider colder climates than pre-industrial (including glacial cycles), and warmer periods than  
 2943 pre-industrial separately, with the Last Glacial Maximum (LGM; ~20 thousand years ago) and mid-  
 2944 Pliocene Warm Period (mPWP; 3.3-3.0 million years ago) being the best known and most  
 2945 comprehensively studied examples. In accordance with section 2, we develop estimates for a  
 2946 likelihood function of the temperature change and priors on the forcings. Our basic approach is to  
 2947 generate ranges that encapsulate the range of plausible estimates presented in the literature.  
 2948 These are expressed in the form  $N(X,Y)$ , which is a Gaussian distribution with mean  $X$  and  
 2949 standard deviation  $Y$  (all uncertainties are 1 standard deviation unless otherwise stated). We then  
 2950 calculate sensitivity likelihoods based on these constraints using the modified versions of equation  
 2951 (3). The modifications to equation (3) are necessarily different in form for the cold and warm  
 2952 periods due to the different level of evidence, and the differing approaches in published research.  
 2953 Information from other intervals can, in principle, be included following a similar style of argument,  
 2954 especially as further detailed records through older intervals of the last 1 to 2 million years emerge,  
 2955 and as greater spatial coverage is developed. As an additional example, and as supporting

2956 evidence, we show the results obtained from analysis of the very warm period of the Paleocene-  
2957 Eocene Thermal Maximum (PETM), but this is not used in our final estimate.

2958  
2959 As discussed in section 5.1, there is considerable uncertainty in measurements of climate  
2960 variables gleaned from paleoclimate. Therefore, researchers interested in climate sensitivity have  
2961 focused on intervals in the past when temperatures and greenhouse gas forcings have been very  
2962 different to those of today and thus where the signal is also large. In sections 5.2 and 5.3 we  
2963 present numerical values based primarily on our expert assessment of the relevant literature. We  
2964 then combine the information in section 5.4 to produce a likelihood function for  $S$  based on  
2965 paleoclimate information.  
2966

## 2967 **5.1 Estimating climates in the past—methods and** 2968 **sources of uncertainty**

2969  
2970 The methods for obtaining paleoclimate changes and forcings from geologic evidence are less  
2971 direct than those using the instrumental record. This results in considerable additional uncertainty,  
2972 much larger than the uncertainty for direct measurements over the last few hundred years. We  
2973 outline some of the methods and sources of uncertainty here. Reducing the uncertainties has the  
2974 potential to lead to major improvement in future estimates of climate sensitivity using evidence  
2975 from the geological past.  
2976

2977 In practical terms, continental ice-sheet variations are approximated using global sea-level  
2978 reconstructions and modelling (Clark and Mix, 2002; Clark and Tarasov, 2014; Lambeck et al.,  
2979 2006, 2010, 2014, 2017; Hansen et al., 2007, 2008, 2013; de Boer et al., 2010, 2012, 2014;  
2980 Rohling et al., 2012, 2017; Grant et al., 2014). Vegetation and land-surface changes are very  
2981 poorly constrained. For a few rare intervals, large scale biome reconstructions have been  
2982 produced (typically ~125,000, ~20,000 and ~6,000 years ago; Prentice et al., 1993; Harrison et al.,  
2983 1995, 2003; Wu et al., 2007; Bartlein et al., 2011; Hopcroft and Valdes, 2015; Kageyama et al.,  
2984 2017; Otto-Bliesner et al., 2017). It is very difficult to obtain sufficiently dense global networks of  
2985 well-dated pollen data for such exercises; even for the well-studied LGM a robust vegetation map  
2986 has yet to be developed. High-resolution dust-aerosol records exist from only a few locations, and  
2987 mostly from the very remote polar regions (ice-core records; Lambert et al., 2008; Schüpbach et  
2988 al., 2018). Although dust is being incorporated in models (Kageyama et al., 2017; Otto-Bliesner et  
2989 al., 2017), and quality dust-flux records from downwind of the dominant source regions (the world's  
2990 great deserts) are being developed, a high density of such records is needed because dust is  
2991 poorly homogenized in the atmosphere; it mainly influences the radiative balance close to, and  
2992 downwind of, the source regions.  
2993

2994 Past estimates of climate properties from direct measurements of atmospheric composition  
2995 comprise only greenhouse gas concentrations ( $\text{CO}_2$ ,  $\text{CH}_4$ , and to some extent also  $\text{N}_2\text{O}$ ) in air  
2996 bubbles preserved in ice cores. The oldest records, from Antarctic ice cores, cover the last  
2997 800,000 years (Siegenthaler et al., 2005), and there is some further information as far back as 1  
2998 million years ago from shallow blue ice samples in Antarctica (Higgins et al., 2015; Yan et al.,  
2999 2019). For other properties, including  $\text{CO}_2$  concentrations, so-called “proxy” measurements are  
3000 used, which are empirically calibrated to climate properties on the basis of their modern spatial

3001 distributions and/or on the basis of calculations through the underpinning physical or chemical  
3002 relationships (notably Boron-isotope data; see below).

3003 For properties that are less globally homogeneous (e.g., sea level, land ice sheets, or  
3004 temperature), some level of modelling is required to transform sparse measurements into global  
3005 estimates. Such models vary in complexity, from a simple metric for latitudinal variation, smoothing  
3006 towards present-day patterns, or utilizing patterns from paleoclimate simulations with state-of-the-  
3007 art climate models. In all cases, the community aims to develop a variety of independent proxies  
3008 for each predominant climate property (for a CO<sub>2</sub> example, see Dyez et al., 2018; Badger et al.,  
3009 2019), so that confidence in individual measures may be evaluated through comparison. This is  
3010 important because certain climate proxies may, for example, be affected by changes through time  
3011 in initial seawater ratios of the elements or isotopes used, or respond non-linearly to change in the  
3012 controlling climate property (with one end of the relationship relatively insensitive to change, so  
3013 that the proxy loses fidelity, or saturates). Cross-validation is especially valuable if it can be  
3014 performed between a proxy and direct measurements from ice cores; a key example concerns the  
3015 validation of CO<sub>2</sub> reconstructions from the Boron-isotope proxy by intercomparison with direct  
3016 measurements of CO<sub>2</sub> changes from ice cores (e.g., Martínez-Botí et al., 2015; Chalk et al., 2017;  
3017 Honisch et al., 2005; Foster, 2008; Raitzch et al., 2018).

3018 Another issue with proxies is that many rely on fossilizing biological signal carriers (e.g.,  
3019 foraminifera or concentrations of specific biomarkers), which implies a dependence over time on  
3020 species-specific behaviors, ecological niche changes, and biomineralization pathways. The  
3021 impacts of these issues are commonly minimized by limiting analyses to a single, well-defined  
3022 species or biomolecule, but further back in time we are inevitably dealing with species that are no  
3023 longer extant. Ecological equivalence is commonly assumed (mostly based on shape and shell-  
3024 development similarities), supported by whole-assemblage evaluations of the entire suite of past  
3025 species' ecological niche occupations relative to one another (commonly using stable oxygen and  
3026 carbon isotopes). However, working with extinct species in ancient time intervals clearly introduces  
3027 greater uncertainty than working with species alive today.

3028 Finally, good chronology (dating) is essential when comparing records of different proxies or ice-  
3029 core data. Here, relative age equivalence is even more important than absolute age control: for  
3030 evaluating paleoclimate sensitivity, past (proxy) values of climate forcing factors need to be  
3031 compared to synchronous values of temperature, no matter what the absolute age of the interval  
3032 is. Chronological control for such records is best in the past 40,000 years, when radiocarbon dating  
3033 is available, and age uncertainties are only up to a century or two in the best cases (Reimer et al.,  
3034 2013; Hogg et al., 2013). Next best control exists for the last glacial cycle (past 100,000 years),  
3035 with strong constraints from ice-core chronologies from Greenland and the West Antarctic,  
3036 supported by U-series dated cave deposits, allowing comparisons between records with age  
3037 uncertainties of the order of at best 500 years (e.g., Shackleton et al., 2000; Grant et al., 2012;  
3038 WAIS Divide Project Members, 2015; Marino et al., 2015). In older levels still, down to half a million  
3039 years ago or so, combined application of U-series dated cave-deposits and astronomical time-  
3040 scale tuning of exceptionally rhythmic sedimentation systems (like that in the Mediterranean)  
3041 provide a sound level of age control with uncertainties of the order of  $\pm 1000$  to 2000 years (Grant  
3042 et al., 2014). Targeted use of events, such as instantaneous volcanic ash deposits, can provide  
3043 selected intervals of improved control relative to the uncertainties stated above. But it is evident  
3044 that comparison between records is hindered to some extent by chronological control, which by  
3045 itself introduces an unavoidable portion of uncertainty in calculated paleoclimate sensitivity  
3046 estimates.

3047 The types of proxies used for estimating climate variables for cold periods over the last 800kyr are  
3048 mostly different from those used for the warm periods further back in time. This means that we  
3049 may expect uncertainties for these cold and warm periods, which we evaluate separately below, to  
3050 be largely independent.  
3051

## 3052 **5.2 Evidence from cold periods: LGM and glacial-** 3053 **interglacial transitions**

3054  
3055 Glacial-interglacial cycles of the Pleistocene (last 2.5 million years) are best known from the last  
3056 half million years. Over that time they were characterized by well documented CO<sub>2</sub> fluctuations  
3057 between ~180 and ~280 ppm (Siegenthaler et al., 2005; we quote all gas concentrations by  
3058 volume), and methane fluctuations between ~350 and ~700 ppb (Loulergue et al., 2008). Sea-  
3059 level/ice-volume fluctuations took place over a total range of about -130 to +10 m (e.g., Rohling et  
3060 al., 2009, 2014; Grant et al., 2014).

3061 We focus mostly on the Last Glacial Maximum (LGM, between 19,000 and 23,000 years before  
3062 present) as it is the most recent quasi-stable cold period, and has been extensively studied.  
3063 Relative to other, earlier but similarly cold, glacial maxima there is a wealth of data available for the  
3064 LGM from both paleo-archives and modelling studies.

3065 In this section, the focus is on summarizing our understanding of paleoclimates using information  
3066 from observations and modelling in order to derive priors on  $\Delta F$ , and likelihoods for  $\Delta T$  for different  
3067 intervals. For all temperature changes and forcings in this section, we use a Gaussian error  
3068 distribution, and give the uncertainty as one standard deviation, unless otherwise indicated.  
3069

### 3070 **5.2.1 Surface temperature change $\Delta T$**

3071  
3072 Last Glacial to interglacial global mean temperature change estimates have been much studied  
3073 and remain debated. Across studies, the inferred range is between ~3 and ~7 K below pre-  
3074 industrial with little probability of lying outside this range (MARGO, 2009; Annan and Hargreaves,  
3075 2013; Schmittner et al., 2011; Rohling et al., 2012; Hansen et al., 2007; Köhler et al., 2010;  
3076 Masson-Delmotte et al., 2010; Friedrich et al., 2016; Snyder, 2016a). We therefore take  $N(-5,1)$  as  
3077 our observational likelihood of the temperature change.  
3078

### 3079 **5.2.2 Forcings contributing to $\Delta F$**

3080  
3081 Radiative forcing at the LGM consists of several components, and we describe the most significant  
3082 of these here. Note that changes in global annual mean orbital forcing are negligible ( $\sim 0.1 \text{ W m}^{-2}$ ),  
3083 although regional and seasonal changes range from  $-9 \text{ W m}^{-2}$  to  $-3 \text{ W m}^{-2}$  (Kageyama et al.,  
3084 2017). Here we consider estimates from the literature, and estimate values for these forcings, in  
3085 order to calculate an overall best estimate for the total forcing. Some of the literature also provides  
3086 quantitative uncertainty estimates, which we use as an approximate guide, although finally we use  
3087 a somewhat larger value to reduce the possibility of overconfidence in our estimate.

3088 Lower GHG concentrations are well characterized for the LGM. Here we use the latest  
3089 PMIP4/CMIP6 LGM estimates of  $[\text{CO}_2] = 190 \text{ ppm}$ ,  $[\text{CH}_4] = 375 \text{ ppb}$  and  $[\text{N}_2\text{O}] = 200 \text{ ppb}$   
3090 (Kageyama et al., 2017). For the pre-industrial greenhouse gases, we use the CMIP6 estimates for  
3091 1850 (Meinshausen et al., 2017),  $[\text{CO}_2] = 284 \text{ ppm}$ ,  $[\text{CH}_4] = 808 \text{ ppb}$ , and  $[\text{N}_2\text{O}] = 273 \text{ ppb}$ . The  
3092 forcing formulae from Etminan et al. (2016) translate these concentrations into  $\text{CO}_2$ :  $-2.16 \text{ W m}^{-2}$ ,  
3093  $\text{CH}_4$ :  $-0.37 \text{ W m}^{-2}$ , and  $\text{N}_2\text{O}$ :  $-0.27 \text{ W m}^{-2}$ . However, in line with the discussion in section 3.2.1 we  
3094 increase the greenhouse gas forcings by 5% to account for the land warming effect (tropospheric  
3095 and surface albedo adjustments). They therefore become  $-2.27$ ,  $-0.39$  and  $-0.28$  respectively.  
3096 Because the forcing due to a doubling of  $\text{CO}_2$ ,  $\Delta F_{2\times\text{CO}_2}$ , is considered uncertain in our analysis (with  
3097 a central estimate of  $4.0 \text{ W m}^{-2}$ , see section 3.2.1), we represent the  $\text{CO}_2$  component of the forcing  
3098 as  $-2.27/4.0 = -0.57 \Delta F_{2\times\text{CO}_2}$  in our calculation. We further increase the  $\text{CH}_4$  value by 45% to  
3099  $-0.57 \text{ W m}^{-2}$  to account for ozone and stratospheric water vapor effects (following Hansen et al  
3100 2005).

3101  
3102 Forcing from the large ice sheets, via albedo and elevation changes (lapse rate feedback) and the  
3103 concomitant drop in sea level, have been estimated at around  $-3.2 \text{ W m}^{-2}$  by the IPCC AR4  
3104 (Hegerl et al., 2007) and  $-3.7 \text{ W m}^{-2} \pm 0.7 \text{ W m}^{-2}$  in a review by Köhler et al. (2010). The single  
3105 model analysis of Friedrich et al. (2016) obtains a rather lower value of  $-1.6 \text{ W m}^{-2}$  for the ice  
3106 sheet forcing, which they ascribe to the effect of cloud cover substantially masking the ice albedo  
3107 change. The climate models that participated in the second and third Paleoclimate Model  
3108 Intercomparison Projects (PMIP2 and PMIP3) have values from  $-2.6$  to  $-3.5 \text{ W m}^{-2}$  (PMIP2,  
3109 Braconnot et al., 2012) and from  $-3.6$  to  $-5.2 \text{ W m}^{-2}$  (PMIP3, Braconnot and Kageyama, 2015).  
3110 The different ice-sheet reconstruction used for PMIP2 and PMIP3 led to a difference in forcing of  
3111 about  $-1 \text{ W m}^{-2}$  (Abe-Ouchi et al., 2015). We represent this evidence with an estimate of  $-3.2$   
3112  $\text{W m}^{-2} \pm 0.7 \text{ W m}^{-2}$ .

3113 The radiative impact of changes in vegetation is estimated to be  $-1.1 \pm 0.6 \text{ W m}^{-2}$  (Köhler et al.,  
3114 2010; Rohling et al., 2012; and references therein). A variety of estimates have been made of the  
3115 forcing due to the glacial increase in atmospheric dust loadings, with a range of best estimates of  
3116  $0.1$  to  $-2.0 \text{ W m}^{-2}$  (Yue et al 2011; Takemura et al 2009; Albani et al 2014; Ohgaito et al., 2018;  
3117 Hopcroft et al., 2015; Mahowald et al., 2006; Köhler et al., 2010; Rohling et al., 2012; Claquin et al  
3118 2003). While some research suggests that models tend to overestimate the influence of dust  
3119 because of an inappropriate distribution of grain size and shape (Kok et al., 2017), we use a range  
3120 of  $-1.0 \pm 1 \text{ W m}^{-2}$  at one standard deviation in order to include the full range of published results with  
3121 a significant likelihood that the forcing is outside that range.

3122 Having separated out the  $\text{CO}_2$  forcing as  $-0.57 \Delta F_{2\times\text{CO}_2}$ , the rest ( $\Delta F$ ) sums to  $-6.15 \text{ W m}^{-2}$ ,  
3123 consisting of  $-3.2 \text{ W m}^{-2}$  (ice sheet),  $-0.57 \text{ W m}^{-2}$  ( $\text{CH}_4$ ),  $-0.28 \text{ W m}^{-2}$  ( $\text{N}_2\text{O}$ ),  $-1.1 \text{ W m}^{-2}$   
3124 (vegetation) and  $-1.0 \text{ W m}^{-2}$  (dust). Our maximum likelihood estimate for total forcing is therefore  
3125  $-8.43 \text{ W m}^{-2}$ . Köhler et al. (2010) also suggest that additional, less commonly discussed factors,  
3126 such as surface albedo change due to shelf exposure related to glacial sea-level lowering, bring  
3127 the total glacial–interglacial radiative forcing closer to  $-10 \text{ W m}^{-2}$ . Models from PMIP2 suggest that  
3128 the albedo effect of exposed shelf is  $-0.7$  to  $-1.3 \text{ W m}^{-2}$  (Braconnot et al., 2012). Friedrich et al.  
3129 (2016) estimate a substantially weaker total forcing of  $-7.6 \text{ W m}^{-2}$ , largely due to weaker ice sheet  
3130 forcing, and Rohling et al. (2012) estimate  $-8 \text{ W m}^{-2}$  (with a plausible range of  $-6.25$  to  $-9.75$   
3131  $\text{W m}^{-2}$ ). Combining in quadrature the uncertainty ranges provided by Köhler et al. (2010) for the  
3132 components of the forcing generates a nominal uncertainty of  $\pm 1.4 \text{ W m}^{-2}$ . However this calculation  
3133 ignores nonlinearity in the addition of different forcings (for which there is limited evidence, but it  
3134 may be significant; e.g., Yoshimori et al., 2009), and also may not account fully for the range of  
3135 published estimates. To account for this, we use a somewhat larger overall uncertainty estimate of

3136  $\pm 2 \text{ W m}^{-2}$  (1-sigma). In sum, we use  $N(-8.43, 2) \text{ W m}^{-2}$  as our observational estimate of the forcing  
3137 change.  
3138

### 3139 **5.2.3 Corrections for state-dependence of sensitivity and slowness of** 3140 **equilibration**

3141

3142 A direct application of energy balance equation ( 3) thus points to a moderate sensitivity of  
3143 around 2.4 K having highest likelihood (i.e.,  $5 \times 4.0 / 8.43$ ; see dashed line in Fig. 15).  
3144 However, such a calculation rests on the assumption that feedbacks remain constant over a wide  
3145 range of climate states and forcings. This has been the approach generally taken in paleodata-  
3146 based studies (Hansen et al., 2007; Köhler et al., 2010; Masson-Delmotte et al., 2010;  
3147 PALAEOSENS, 2012; Rohling et al., 2012; Martínez-Botí et al., 2015). However, it is increasingly  
3148 being questioned by studies concerned with potential state-dependence of paleoclimate sensitivity  
3149 (Zeebe, 2013; von der Heydt et al., 2014, 2016; Köhler et al., 2015; Friedrich et al., 2016; Rohling  
3150 et al., 2018; Stap et al., 2019). Several of these studies suggest that the relationship between  
3151 forcing and temperature response might not be linear, indicating that sensitivity depends on the  
3152 background climate state and/or the efficacy of the forcings.

3153 Quantitative estimates of feedbacks through glacial cycles suggest that, for the LGM, the  
3154 difference due to the nonlinearity may be of the order  $0.5 \text{ W m}^{-2} \text{ K}^{-1}$ , both in models (Crucifix 2006;  
3155 Yoshimori et al., 2009; Yoshimori et al., 2011; IPCC, 2013) and in data from observations  
3156 (Friedrich et al., 2016; Köhler et al., 2015; Köhler et al., 2018), though there are large uncertainties  
3157 in these estimates. Most analyses suggest stronger net feedback for glacial states (i.e.,  $\lambda$  more  
3158 negative, implying a lower sensitivity), but even this is not certain. We parameterize this  
3159 uncertainty in feedback through an additive term which is linear with temperature change; i.e., the  
3160 local feedback at temperature anomaly  $\Delta T$  is given by  $\lambda + \alpha \Delta T$  where  $\alpha$  is an uncertain parameter  
3161 and  $\lambda$  is the feedback for the modern state. The total radiative anomaly relative to equilibrium  
3162 arising from a temperature anomaly of  $\Delta T$  is then given by the integral of this varying feedback  
3163 which amounts to  $\lambda \Delta T + \alpha/2 \Delta T^2$ . Based on the above references, we choose our prior for  $\alpha$  to be  
3164  $N(0.1, 0.1)$  which implies a mean change in feedback of  $-0.5 \text{ W m}^{-2} \text{ K}^{-1}$  at an estimated glacial  
3165 cooling of  $-5 \text{ K}$ , with a likely range of 0 to  $-1 \text{ W m}^{-2} \text{ K}^{-1}$  and a significant chance of exceeding  
3166 these limits.

3167 Additional to this non-constancy in feedback strength, we also account for uncertainty in relating  
3168 the quasi-equilibrium response to the regression-based (see section 2.1) estimate of  $S$ . Modelling  
3169 experiments (Rugenstein et al 2019a,b; and see section 2.1) suggest modest differences between  
3170 the long-term equilibrium sensitivity and our target  $S$  based on regression of an abrupt  $4\times\text{CO}_2$   
3171 simulation. We use the symbol  $\zeta$  to represent this difference, with  $1+\zeta$  therefore being the ratio of  
3172 our target  $S$  to the long-term equilibrium (eq. 8). The mean value of  $1+\zeta$  is 1.06, arising from the  
3173 eight models for which these estimates are available, suggesting that sensitivity as inferred from  
3174 the quasi-equilibrium paleoclimate states considered here is slightly larger than the target  $S$  for this  
3175 assessment. Because this result is obtained from a small ensemble, we use a slightly inflated  
3176 uncertainty of 0.2 relative to the ensemble spread of 0.15.

3177 We include these effects via modifications to the basic energy balance equation ( 3), writing,

3178 
$$\Delta T = \frac{-(-0.57 \Delta F_{2\times\text{CO}_2} + \Delta F')}{\frac{\lambda}{1+\zeta} + \frac{\alpha}{2} \Delta T} \quad (22) \quad ,$$

3179 where the term  $\alpha\Delta T/2$  represents a state-dependence in the sensitivity, and  $1+\zeta$  represents the  
3180 transfer between the long-term quasi-equilibrium and the target  $S$ .  $S$  may then be derived from  $\lambda$   
3181 via equation (4).

3182 The resulting likelihood is shown in Fig. 15, plotted in terms of  $S$ . The maximum likelihood value  
3183 is at 2.5 K, dropping to about 0.1 at 1 K and 0.35 at 6 K (relative to our maximum likelihood value  
3184 of 1).

3185

## 3186 5.2.4 Discussion

3187 We now consider the consequences of low or high climate sensitivity for our understanding of the  
3188 Earth system. Low present-day sensitivity to  $\text{CO}_2$  would require some combination of low cooling at  
3189 the LGM (note, however, that there is little scope for the LGM temperature change to be less than  
3190 3 K because that is the value inferred from observations at low latitudes) and larger-than-estimated  
3191 forcing and/or large response to non- $\text{CO}_2$  forcings, of which the ice-sheet albedo is dominant. A  
3192 larger than expected difference between our target  $S$  and the paleo equilibrium sensitivity (i.e.,  
3193 large  $1+\zeta$ ) would also make low  $S$  somewhat more likely. Total  $\text{CO}_2$  and other GHG forcing is well  
3194 constrained at just under  $-3 \text{ Wm}^{-2}$  at the LGM, and modelled responses to such forcing are close  
3195 to linear when other boundary conditions are held fixed (i.e. pre-industrial ice sheets, etc.) (Hansen  
3196 et al., 2005). A low climate sensitivity of, say, 1 K per  $\text{CO}_2$  doubling together with a true  
3197 temperature anomaly of  $-3 \text{ K}$  (at the very low end of the observed range) would require a very  
3198 large additional radiative forcing effect of ice sheets (around  $-8 \text{ Wm}^{-2}$ ) to generate the additional  
3199 2K or more of cooling. While few detailed factor analyses have been performed, estimates of the  
3200 radiative effect of the continental ice sheets are typically of the order  $-2$  to  $-4 \text{ Wm}^{-2}$  (e.g., Köhler et  
3201 al., 2010; Köhler et al., 2015); i.e., at least a factor of two less than would be required to support a  
3202 low climate sensitivity. Furthermore, models do not tend to exhibit such a strong response to ice  
3203 sheets; instead they suggest that—if anything—the total effect of multiple forcings is generally  
3204 smaller than the linear sum of responses to forcings individually (Yoshimori et al., 2009; Pausata et  
3205 al., 2011; Shakun, 2017). These arguments are consistent with our inferred low relative likelihood  
3206 of 0.2 at  $S = 1$  (Figure 15).

3207 High sensitivity to  $\text{CO}_2$  of around 6 K per  $\text{CO}_2$  doubling could be supported by a cooler LGM  
3208 temperature anomaly of around  $-7 \text{ K}$  (the higher end of the range suggested from proxy-data  
3209 evaluations; e.g., Snyder, 2016a), together with a muted response to non- $\text{CO}_2$  forcings and/or  
3210 substantial nonlinearity with respect to forcing magnitude (i.e., large values of  $\alpha$  in equation 22).  
3211 Since  $\text{CO}_2$  alone would lead to a cooling of 4 K in this case, this would imply a limited (3 K) impact  
3212 of the ice sheets and other forcings (around  $-2 \text{ Wm}^{-2}$ ; less than half of what has been previously  
3213 estimated). This appears to be consistent with our likelihood of 0.3 for  $S = 6 \text{ K}$  (Fig. 15). This  
3214 picture is supported by evidence that spans the most recent five glacial cycles (Rohling et al.,  
3215 2012), and we do not have conflicting evidence from other cold periods. Further back in time,  
3216 uncertainties are greater as the data are substantially poorer; prior to the Pleistocene we have to  
3217 go back 280 million years to find a period when Earth's temperature was much colder than pre-  
3218 industrial (Royer et al., 2004; Montañez and Poulsen, 2013).

3219 We note that the climate models included in the second and third Paleoclimate Model  
3220 Intercomparison Projects (PMIP2 and PMIP3) had climate sensitivities in the range of around 2-5  
3221 K. Emergent constraint analyses have found at best a weak relationship between the cooling  
3222 exhibited in each simulation and the equilibrium sensitivity of the models (Hargreaves et al., 2012;  
3223 Masson-Delmotte et al., 2013; Hopcroft and Valdes, 2015), due to model uncertainty in processes

3224 that are important for the LGM but not related to future climate change, such as the influence of the  
3225 ice sheets (Crucifix, 2006; Hopcroft and Valdes, 2015). All of these models lie in the high likelihood  
3226 region of our main result and we therefore do not expect to be able to discriminate strongly  
3227 between them.

## 3228 **5.3 Evidence from warm periods**

### 3229 **5.3.1 Warm periods—mid-Pliocene:**

3230 The mid-Pliocene warm period (mPWP) occurred over the interval of 3.3-3.0 million years ago, and  
3231 is the most recent time in the past when CO<sub>2</sub> concentrations are thought to have been high enough  
3232 to be comparable to present-day values. During this time, there were orbital cycles with periods of  
3233 40,000 years, during which CO<sub>2</sub> levels inferred from high-resolution boron isotope data varied  
3234 between ~300 and ~400 ppmv (e.g., Martínez-Botí et al., 2015), and sea level fluctuated by about  
3235 30 m (Rohling et al., 2014). Other CO<sub>2</sub> proxies are less conclusive, partly because they have not  
3236 yet been measured in sufficient resolution to distinguish individual orbital cycles (Dyez et al.,  
3237 2018). Despite progress in recent years, both the GHG forcing and the global temperature  
3238 response during the mPWP warm intervals remain uncertain. Here we analyze the mPWP, in order  
3239 to provide inputs to equation ( 3), in a similar way to the LGM analysis above.

3240

#### 3241 **5.3.1a Surface temperature change $\Delta T$**

3242

3243 Following initial global assessments (Haywood et al., 2010), where SSTs were judged to be higher  
3244 than Holocene values by about 0.8 K in the tropics, rising to 1.7 K globally, Pliocene SSTs have  
3245 been considerably revised to higher values, particularly in the tropics (e.g. Zhang et al., 2014;  
3246 O'Brien et al., 2014). Compilations that focus on the more reliable geochemical proxies now place  
3247 mean tropical SST during warm intervals of the Pliocene at +1.5 K, relative to the Holocene  
3248 (Herbert et al., 2010). Further refinements are likely to push this estimate even higher (e.g. O'Brien  
3249 et al., 2014; DeNezio et al., 2009). The compilation of Rohling et al. (2012) reveals that tropical  
3250 SST change is ~50% of the global mean change over the last 0.5 Myr, a value that is also  
3251 consistent with the PMIP3 ensemble at the LGM. Applying that to the mid Pliocene suggests a  
3252 mean global surface air temperature increase of around 3K relative to the Holocene (although this  
3253 value still has substantial uncertainty, and we therefore represent our temperature likelihood as  
3254 N(3, 1) K).

3255

#### 3256 **5.3.1b Forcings contributing to $\Delta F$**

3257

3258 Climate forcing during the mPWP is likely dominated by CO<sub>2</sub>, but other forcings must also be  
3259 considered, as for the LGM (i.e., Unger and Yue, 2013). There remains considerable uncertainty  
3260 regarding all GHG concentrations. PlioMIP, the Pliocene Model Intercomparison Project, assumed  
3261 a value of 405 ppm CO<sub>2</sub>, which is at the high end if considering CO<sub>2</sub> alone, but which was chosen  
3262 to implicitly include the effect of other well-mixed GHGs.

3263 To bracket most reported values we set a value of N(375, 25) ppm for CO<sub>2</sub> and assume that N<sub>2</sub>O  
3264 and CH<sub>4</sub> together represent an additional 40%± 10% of forcing (Hansen et al., 2013; Martínez-Botí  
3265 et al., 2015; Sossian et al., 2018), which results in a best estimate for total forcing of 2.2 W m<sup>-2</sup>



3266 with an uncertainty of  $0.6 \text{ W m}^{-2}$  at one standard deviation (not precisely Gaussian), relative to the  
3267 284 ppm pre-industrial state due to well-mixed GHGs.

3268 Since our aim is to estimate the short-term response due to carbon dioxide change, we need to  
3269 consider the influence of other forcings. In other words we need to consider the difference between  
3270 the Earth System Sensitivity (ESS, see section 2.1) and S. If the forcings were individually well  
3271 known then we could do this directly by including them in the energy balance equation as we did  
3272 for the LGM. However, forcings such as changes in ice sheets and vegetation are difficult to  
3273 quantify in detail, and tectonic and/or orographic forcings relative to the present complicate the  
3274 assumption that all feedbacks were driven by  $\text{CO}_2$  change (Lunt et al, 2010). For example,  
3275 uncertainties remain with respect to the overall sizes and temporal variability of ice sheets. With  
3276 Pliocene sea level at least 6m above the present (Dutton et al., 2015), we know that ice sheets  
3277 were smaller, but the upper boundary for sea level remains unclear (Dutton et al., 2015) as does  
3278 the Pliocene glacial-interglacial amplitude variability (Naish et al., 2009; de Boer et al., 2010; Miller  
3279 et al., 2012; Rohling et al., 2014; Stap et al., 2016). Overall, sea-level estimates (as available at  
3280 the time of study) at times with  $\sim 375$  ppm  $\text{CO}_2$  reveal a median at +21 m and asymmetrical 68%  
3281 and 95% probability envelopes of 9-27 m and 1-33 m, respectively (Foster and Rohling, 2013). In  
3282 addition, the "time slab" approach used in PlioMIP (where data from warm intervals within the  
3283 longer period are amalgamated to form a single climatology) introduces further uncertainties, for  
3284 example, regarding the regional influence of orbital changes. These are in the process of being  
3285 quantified more carefully (Haywood et al., 2016; Dowsett et al., 2016) and time series approaches  
3286 similar to those developed for the last 800 kyr are also beginning to be applied to the mPWP (e.g.,  
3287 Martínez-Botí et al., 2015).

3288 Since we do not have accurate estimates of the ice sheet and vegetation forcings, we instead use  
3289 an uncertain parameter to represent the amount by which these (generally slower) responses  
3290 inflate the response that would be generated by  $\text{CO}_2$  alone. Lunt et al (2010) argue that this ratio  
3291 ESS/S is around 1.4 for the Pliocene based on simulations using HadCM3, while Haywood et al  
3292 (2013) find an ensemble mean ratio of 1.5 with considerable variation between models but with a  
3293 total range of 1 to 2 across the models in the PlioMIP1 ensemble. We represent these results  
3294 with an ESS inflation factor  $1 + f_{ESS}$  where  $f_{ESS}$  is distributed as  $N(0.5, 0.25)$ .

3295 We thus represent the energy balance of the climate system for the Pliocene as

3296 
$$\Delta T = \frac{-\Delta F_{\text{CO}_2} (1+f_{\text{CH}_4}) (1+f_{\text{ESS}})}{\frac{\lambda}{(1+\zeta)}} \quad (5.2)$$

3297 where  $\Delta F(\text{CO}_2)$  is the forcing due to  $\text{CO}_2$  (i.e.,  $\ln([\text{CO}_2]/284)/\ln(2) \times \Delta F_{2\times\text{CO}_2}$ ),  $1+f_{\text{CH}_4}$  is the additional  
3298 forcing due to methane and  $\text{N}_2\text{O}$ , which equals  $(1+N(0.4, 0.1))$ , and  $1+\zeta$  represents the transfer  
3299 between quasi-equilibrium and regression estimate of feedback.

3300 The resulting likelihood is shown in Figure 16 and has a maximum likelihood S of around 3.2 K.

3301

### 3302 5.3.1c Discussion

3303

3304 As in section 3.2.4, we now consider storylines that could explain low and high values for the  
3305 sensitivity. A low climate sensitivity would require some combination of lower temperature change  
3306 and/or greater response to non-GHG/non- $\text{CO}_2$  forcing. An mPWP global mean warming of 1 K  
3307 would suggest a sensitivity of about 1.2 K per  $\text{CO}_2$  doubling, but this requires that we ignore the  
3308 known low-temperature bias of some paleo-thermometers (e.g., O'Brien et al., 2015). This is a low-

3309 likelihood scenario, although uncertainties in orbital forcing influences make it hard to be sure. Our  
3310 calculation as presented in Figure 16 gives a likelihood of 0.3 at  $S = 1.2$  K per CO<sub>2</sub> doubling.

3311 On the other hand, if the GHG forcing were lower than recent estimates (e.g., Martínez-Botí et al.,  
3312 2015), then a high sensitivity is quite easily reconciled with the data. For example, the lowest CO<sub>2</sub>  
3313 estimates within the mPWP reach as low as 330 to 350 ppm (Pagani et al., 2010; Martínez-Botí et  
3314 al., 2015; Dyez et al., 2018). Relative to pre-industrial conditions, 350 ppm (with associated  
3315 changes in CH<sub>4</sub> and N<sub>2</sub>O) only represents  $1.7 \text{ W m}^{-2}$ . For that value, 2 K warming would imply a  
3316 sensitivity of nearly 4.5 K per CO<sub>2</sub> doubling, and 3 K would suggest a sensitivity of  $\sim 6.5$  K per CO<sub>2</sub>  
3317 doubling. If the CO<sub>2</sub> forcing were as small as 330 ppm, these values would shift to 6 K and 9 K,  
3318 respectively. Such a low forcing is considered unlikely, and would require a minimal to non-existent  
3319 role for non-CO<sub>2</sub> forcing during the mPWP. Our mPWP likelihood is around 0.4 at 6 K and drops to  
3320 0.2 at  $S = 8$  K per CO<sub>2</sub> doubling.

3321 As was the case in section 4.1, some models have been used to perform simulations of the mPWP  
3322 as part of PMIP3 (PlioMIP) (Haywood et al., 2013). While all models generated plausible  
3323 simulations for this period, there is little discriminatory power to distinguish between them. This is  
3324 unsurprising given that their climate sensitivities range within the high likelihood range of our  
3325 analysis. Emergent constraints analyses have been performed using these models (Hargreaves et  
3326 al., 2016). While these suggest a climate sensitivity consistent with our results, we do not consider  
3327 them sufficiently robust to further narrow our likelihood, due to the high uncertainty in both model  
3328 boundary conditions and proxy data.

### 3329 **5.3.2 Warm periods—Paleocene-Eocene Thermal Maximum.**

3330

3331 Of the pre-Pliocene warm intervals, the rapid global warming event known as the Paleocene-  
3332 Eocene Thermal Maximum (PETM;  $\sim 56$  Ma) provides perhaps the best opportunity to further  
3333 constrain ECS. Here we explore this opportunity with a comprehensive analysis of the available  
3334 evidence arising from this period. Due to the large uncertainties and the danger of over-  
3335 constraining the likelihood should these be under-estimated, however, we have chosen not to  
3336 include the PETM evidence in our final likelihood estimates. We present the analysis here both  
3337 because it provides supporting evidence to our overall conclusion, and in the hope that it may spur  
3338 future research.

3339 Coincident with a dramatic input of biogenic carbon into the active climate system, warming  
3340 occurred rapidly (in  $<20$  kyr, likely in as little as 4 or 5 kyr; Zeebe et al., 2016; Kirtland Turner et al.,  
3341 2017). Dunkley Jones et al. (2013) compiled available SST data and, comparing these with results  
3342 from a single model, concluded that the global PETM temperature anomaly relative to the early  
3343 Eocene was in the range 4 to 5 K. Incorporating recent SST data from the tropics, Frieling et al  
3344 (2017) estimate a tropical change of 2.7 K with 5.3 K for the global SST anomaly ( $<2$  K very  
3345 unlikely). Using a ratio for global SST to global temperature change of 0.9, based on the results  
3346 from an ensemble of models run for the Eocene Climatic Optimum (EECO  $\sim 50$  Ma) (Lunt et al,  
3347 2013), this gives a slightly higher global temperature estimate of 5.9 K. This suggests a central  
3348 value around 5 K. Relative to the other paleo-intervals discussed in the previous sections,  
3349 relatively few PETM studies have estimated this global value, and uncertainty in the interpretation  
3350 of measurements from so deep in the paleo-record is high. Therefore, despite the closeness of the  
3351 estimates in the literature, our uncertainty in this global value is greater than the equivalent for the  
3352 other intervals considered in the previous sections. Here we use a range of  $N(5, 2)$  K which  
3353 includes the published values within the high likelihood range.

3354 While rapid in geological terms, the time scale for the PETM warming is still sufficiently long for a  
 3355 quasi-equilibrium temperature response to the radiative forcing. The PETM is associated with a  
 3356 global negative  $\delta^{13}\text{C}$  anomaly of around 3-4‰, which is indicative of an injection of a large amount  
 3357 of biogenic carbon into the Earth system driving this warmth, either in the form of  $\text{CO}_2$ ,  $\text{CH}_4$ , or  
 3358 both. Although constraining the  $\text{CO}_2$  change across the PETM is an area of active research, a  
 3359 number of first-order constraints can be formulated for our purposes, based on Earth System  
 3360 Modelling of the  $\delta^{13}\text{C}$  anomaly and accounting for the response of the deep ocean carbonate  
 3361 system, and the carbon isotopic composition of the likely carbon sources (e.g., Cui et al., 2011).  
 3362 This gives a maximum  $\text{CO}_2$  change of 5x (from 800 to 4000 ppm; Cui et al., 2011) and a minimum  
 3363 of 2x  $\text{CO}_2$  (1000 to 2000 ppm). More recent estimates, based on paleo-observations, are  
 3364 consistent with this modelling approach, and suggest a change from about 900 ppm to between  
 3365 1500 ppm and 4100 ppm (95% confidence range), with a central value of 2200 ppm (Gutjahr et al,  
 3366 2017), or a change from about 700–1000 ppm to about 1400-3300 ppm (Schubert and Jahren,  
 3367 2013). Here we model the increase in  $\text{CO}_2$  by assuming a baseline of 900ppm increasing to a  
 3368 Gaussian defined as  $N(2400, 700)$  ppm.

3369 A large uncertainty when using the PETM in this way concerns the magnitude of the change in  $\text{CH}_4$   
 3370 concentration that is potentially associated with the event (e.g., Zeebe et al., 2009). In the absence  
 3371 of firm current constraints on  $\text{CH}_4$  and  $\text{N}_2\text{O}$  concentrations at the PETM, we again use a factor  
 3372 applied to the  $\text{CO}_2$  forcing to account for this additional forcing. Large and sustained inputs of  $\text{CH}_4$   
 3373 directly into the atmosphere have the potential to extend the lifetime of  $\text{CH}_4$  in the troposphere by  
 3374 up to a factor of 4 (Schmidt and Shindell, 2003), so the impact of  $\text{CH}_4$  on PETM temperatures can  
 3375 be larger than sometimes assumed. We therefore draw the scaling factor from  $N(0.4, 0.2)$ , which is  
 3376 consistent with our previous assumption for the mPWP but allows twice the uncertainty.

3377 The PETM background climate state differs substantially from the present (for example, there are  
 3378 major differences in paleogeography and the basic state is much warmer), leaving open the  
 3379 possibility of substantial feedback differences between the PETM and the present including slow  
 3380 “Earth system” feedbacks such as vegetation. We have little basis for making a quantitative  
 3381 estimate for this, and therefore include additional uncertainty in the form of an additive term  $\beta$  on  
 3382 the net feedback of magnitude  $N(0, 0.5) \text{ W m}^{-2} \text{ K}^{-1}$ , which has a similar magnitude to the term used  
 3383 for the LGM, although in this case we do not suppose a direct relationship with the amount of  
 3384 warming. The arbitrary nature of this choice, and the possibility that this component could be much  
 3385 more significant, are the main reasons that we do not include the PETM result in the final summary  
 3386 likelihood for  $S$  obtained from paleo-information.

3387 The resulting equation for the PETM therefore has the form

$$3388 \quad \Delta T = \frac{-\ln(\text{CO}_2/900)}{\ln(2)} \frac{\Delta F_{2\times\text{CO}_2} (1+f_{\text{CH}_4})}{\frac{\lambda}{(1+\zeta)} + \beta} \quad (5.3)$$

3389 where  $\Delta F_{2\times\text{CO}_2}$ ,  $\lambda$ ,  $f_{\text{CH}_4}$ , and  $1+\zeta$  are as before and  $\beta$  is the additional state-dependence parameter.

3390

3391 Our likelihood function is shown in Fig. 17 .

3392 The nature of the proxies used to estimate the forcing and climate state at the PETM is very similar  
 3393 to that of the proxies used for the mPWP; they are likely to share some errors and biases. For this  
 3394 reason, we do not consider the PETM information to provide a new, fully independent line of  
 3395 evidence. As a sensitivity test, we consider the case that the uncertainties in  $\text{CO}_2$  and temperature  
 3396 for both periods are correlated at the 80% level. We also assume the same transfer function  $\zeta$ .  
 3397 Under these assumptions, the joint likelihood (Fig. 18 ) is shifted slightly to lower values than the

3398 result obtained in section 5.2.1 for the mPWP alone, with the high-value tail slightly narrower. This  
3399 calculation depends on some highly uncertain parameters for which we have had to make  
3400 somewhat arbitrary judgements, such as the importance of state dependence for the PETM.  
3401 Differentiating between state dependence in the radiative forcing, and in the feedbacks (Caballero  
3402 and Huber, 2013), could be an area of future progress. A recent modelling study found that  
3403 changes in geography, ice, and vegetation may have had large impacts at the Eocene (Baatsen et  
3404 al., 2019; Farnsworth et al., 2019). So, while the calculation shown here may be pessimistic, we  
3405 have no firm basis for asserting a higher level of independence and choose to omit the PETM  
3406 calculation from our overall result, while acknowledging that it does appear to add support to the  
3407 mPWP analysis.

3408

## 3409 **5.4. Combining constraints from warm and cold periods**

3410

3411 As outlined at the end of section 5, the uncertainties in the evidence that form the constraints  
3412 described in sections 5.1 and 5.2 above are substantially independent, because the ways in which  
3413 the greenhouse gas levels and estimated temperatures are calculated are not very related  
3414 (typically different measurements and proxies are used). There are some dependencies, however,  
3415 which are specifically accounted for. In particular, dependency arises through the parameters  
3416  $\Delta F_{2xCO_2}$  and  $\zeta$ . Performing the Bayesian updating across the full vector of uncertain parameters  
3417 accounts for these dependencies. Tests show that these dependencies between our cold and  
3418 warm period uncertainties hardly affect our results because the uncertainties constitute only a  
3419 small part of the total uncertainty in our result.

3420

3421 The final combined likelihood function including our evidence from both cold and warm states, and  
3422 including the dependencies, is shown in Fig. 19 .

3423

## 3424 **5.5 Summary**

3425

3426 Like the industrial-era warming trend (analyzed in section 4), climate changes that occurred  
3427 naturally during earlier epochs also depended on  $S$ , and can likewise constrain  $S$  if enough is  
3428 known about what drove them. We find that the two most informative time intervals are the Last  
3429 Glacial Maximum cold period (LGM, ~20,000 years ago) and the mid-Pliocene Warm Period  
3430 (mPWP, 3.3-3 Myr ago), although we have also considered previous glacial cycles, and especially  
3431 the Paleocene-Eocene Thermal Maximum warm period (PETM, ~56 Myr ago), to test for  
3432 consistency. The LGM and earlier glacial maxima were 3-7 K colder than the late Holocene (recent  
3433 pre-industrial millennia) because the Earth's orbit favored climatic changes that included large ice  
3434 sheets in the Northern Hemisphere, increasing the planetary albedo, as well as greenhouse gas  
3435 drawdown (largely into the deep oceans). The mPWP was 1-5 K warmer than the Holocene  
3436 due to higher ambient greenhouse gas concentrations as well as smaller ice volume, and the  
3437 PETM was roughly 3-7 K warmer than the baseline Eocene climate due to a geologically rapid  
3438 release of greenhouse gases. Thus, each climate change we have examined had different  
3439 aspects, which helps to provide a more reliable constraint on  $S$ . The paleoclimate data come from  
3440 intervals where the climate was different to today, but fairly stable for several thousand years,  
3441 meaning that slow feedback processes need to be taken into account. By treating these slow  
3442 processes as forcings rather than feedbacks, we are able to make inferences about  $S$ . Both the

3443 temperature changes that are used, and the slow feedback influences that are removed, are  
3444 constrained using indirect proxy records. This introduces considerable uncertainty in the climate  
3445 sensitivity estimates.

3446  
3447 Paleoclimate sensitivity estimates have been made with increasingly detailed documentation of  
3448 what's included and what's uncertain. For cold periods, estimates are predominantly (but not only)  
3449 from the period covered by the ice cores. The availability of ice-core data means that radiative  
3450 forcing estimates are well constrained (including CO<sub>2</sub>, CH<sub>4</sub> and—through a scaling based on  
3451 measurements in parts of the records—N<sub>2</sub>O, and aerosol dust). We summarize that the most likely  
3452 estimate for climate sensitivity for cold periods falls close to 2.5 K. Extreme estimates range from a  
3453 likelihood of about 0.1 at 1 K to a high-end likelihood of about 0.35 at 6 K. Here, the low extreme of  
3454 1 K assumes a glacial temperature anomaly of –3 K, relative to pre-industrial times, which is the  
3455 lowest- magnitude end of estimates available. It also requires a very large radiative forcing  
3456 effect of ice sheets that is some 2 to 4 times larger than typical reconstructions; climate models  
3457 also do not exhibit such a strong response to ice sheets. So the low extreme of 1 K is highly  
3458 unlikely. At the high end, 6 K assumes a glacial temperature anomaly of –7 K, relative to pre-  
3459 industrial times, which is at the extreme end of estimates available. It also requires a radiative  
3460 forcing effect of ice sheets that is less than half of the estimates in most studies. Hence, as high as  
3461 6 K is unlikely, although it has a slightly greater likelihood than the low extreme of 1 K.

3462  
3463 For past warm periods, we suggest a most likely *S* of 3.2 K, with extremes that range from about 1  
3464 to 8 K (likelihoods about 0.2 at each value). We can only give a range for the most likely estimate,  
3465 because of structural uncertainties that remain in mean global surface air temperature increase, in  
3466 non-CO<sub>2</sub> greenhouse gas concentrations, and in global ice volume (sea level). More, and more  
3467 detailed, observational constraints are needed. Our low extreme estimate assumes that  
3468 temperature changes were at the low end of the published spectrum, and that there was a larger  
3469 than commonly anticipated impact of non-GHG/non-CO<sub>2</sub> forcing. For our low extreme of about 1.2  
3470 K, we assumed that mid-Pliocene global mean warming was 1 K, which equates to the present-day  
3471 climate. Though unlikely given Pliocene paleoclimate evidence, this cannot be fully excluded. High  
3472 sensitivities require that mPWP CO<sub>2</sub> levels were at the very low end of published estimates. If we  
3473 then assume that non-CO<sub>2</sub> forcing was negligible, then we find an unlikely but not impossible high  
3474 extreme estimate for *S* of up to 10 K. Information from the PETM broadly supports the estimated  
3475 likelihood obtained using climate information from the Pliocene, but we consider the evidence too  
3476 uncertain for it to be included in the likelihood function.

3477  
3478 Since the dominant uncertainties for warm and cold periods are different (e.g., ice-sheet forcing  
3479 affects cold climates but not warm ones; greenhouse gases are poorly known for deeper time  
3480 warm climates but directly measured from ice cores for more recent cold climates), they provide a  
3481 tighter constraint in combination than separately, even though they are not wholly independent.  
3482 Together, they suggest that *S* is likely to fall within 1.5-5 K, with highest likelihood around 2.5 K.  
3483 These results are fairly similar to those obtained in the PALAEOSENS assessment  
3484 (PALAEOSENS, 2012). The paleoclimate evidence offers significant promise to constrain *S*  
3485 further. In particular, if LGM ice-sheet forcing and global temperature can be better constrained,  
3486 the cold-period evidence could further constrain the upper end of the current range. The PETM is  
3487 an active area of research and it may in future be possible to use evidence for this period with  
3488 more confidence to further constrain sensitivity. There is also a possibility in future of using  
3489 evidence from other intervals such as the Eocene and Miocene. Progress will depend equally on  
3490 further development of biogeochemical paleoclimate modelling to test interpretations of existing  
3491 proxy data, and on collection of more such data.

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## 6. Dependence between lines of evidence

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Combining evidence from multiple lines hinges on a crucial question: are they independent? Some observation, assumption, model (or model component), or unknown influence on climate could have influenced more than one line of evidence or its interpretation. Such mutual influences are inevitable at some level, since all scientists communicate regularly and share views on the climate system. What we are concerned with here is whether there are quantitatively significant co-dependencies across the major evidence lines, and what impact this might have on our results. A pedagogical example was given in section 2.4.1, and each of sections 3-5 has already addressed evidence co-dependencies within the individual, major lines (sections 3.6, 4.1.2, 5.3.2).

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Such co-dependencies may either increase or decrease uncertainty. For example, some unaccounted-for factor might cause two lines of evidence to deviate in the same direction (e.g., pushing both toward a lower apparent  $S$ ), or alternatively push them in opposite directions. In the former case, the true overall uncertainty is larger than if we ignored the co-dependency, while in the latter case it is smaller. In this assessment we will simply ignore co-dependencies that appear to be of the latter, “buffered” variety (a conservative strategy, which could lead us to overestimate uncertainty). But the former, “reinforcing” co-dependencies require attention.

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We are not revisiting here the degree of uncertainty of any one line of evidence, but instead asking whether, if one line of evidence for whatever reason points too low (or too high) in terms of  $S$ , this affects the interpretation of the other lines. For more discussion of this issue and what is meant by independence, see Annan and Hargreaves (2017).

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### 6.1 Use of GCMs

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An obvious suspect for co-dependent errors is our use of GCMs in various ways to interpret or support all three lines of evidence. Over-reliance on these models is hence dangerous, especially since the models may differ systematically from reality in important ways.

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Our use of them, however, arguably relies on different model aspects for each line of evidence. For example, they help constrain feedbacks (section 3) and play a large role in quantifying the historical “pattern effect” (section 4), but the former involves global-mean temperature sensitivity of clouds and other variables, while the latter involves regional departures from the global mean. These could be seen as orthogonal, and indeed appear to be uncorrelated in GCM ensembles (see below); for example, regional SST changes depend strongly on ocean processes (e.g. Kostov et al., 2018) while global feedbacks do not (Ringer et al., 2014). Moreover, both the feedbacks and pattern-effect responses are supported by observations and process understanding. GCMs are also used to estimate adjustments to paleo forcings, but again these involve aspects such as

3535 atmospheric responses to ice sheets and aerosol sources, which would be expected to depend on  
3536 different model processes from those relevant to the other lines. GCM climate sensitivities are not  
3537 directly used (although GCMs do help to constrain some of the feedbacks in section 3); in general,  
3538 these models are used to quantify corrections and secondary effects (and their uncertainties)  
3539 which were neglected in traditional studies.

3540  
3541 Nonetheless some of these “secondary effects” turn out to be large, and there are some potential  
3542 interdependencies between evidence lines, some of which do involve GCMs. These are now  
3543 examined.  
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## 3545 **6.2 Potential co-dependencies**

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3547 The main potential co-dependencies we see are as follows.  
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3549 **GCM model selection bias.** Modelers and process experts are aware of the historical climate  
3550 record. GCM aerosol forcings might have been selected in order to match the observed warming  
3551 rate over the 20<sup>th</sup> century (e.g., Kiehl, 2007), and otherwise plausible models or feedbacks might  
3552 have been discarded because of perceived conflict with this warming rate, or aversion to a model’s  
3553 climate sensitivity being outside an accepted range. If so, any factor causing an error in  $S_{\text{hist}}$  could  
3554 in principle have caused a same-signed error in the process estimates of  $S$ , i.e. a “reinforcing”  
3555 codependency.  
3556

3557 Our strategy for mitigating this is to rely on multiple lines of evidence in assessing the strength of  
3558 key feedbacks (section 3). We find that there is sufficient evidence from observations of present-  
3559 day weather variations and climate variability, process models not used in climate simulations, and  
3560 observational tests of GCMs unrelated to historical warming, to support the process evidence and  
3561 likelihoods presented without relying on their ECS values (see section 6.1). Also, the historical  
3562 evidence (section 4) relies on ‘bottom up’ estimates of aerosol forcing and does not use  
3563 constraints on forcing that arise from temperature trends over the historical record (see section  
3564 4.1.1). In addition, the historical record has been extensively investigated by detection and  
3565 attribution methods, which allow a change in feedback or forcing strength by rescaling the time-  
3566 space pattern of response to best match the observed records. These results (see section 4.1.3)  
3567 support the inferences made from the overall warming and forcing trends. Therefore, the process  
3568 evidence may be considered essentially independent of the other two lines of evidence even if  
3569 climate model development has indeed suffered from selection biases.  
3570

3571 **Transfer function / SST pattern error.** Relating the apparent sensitivities (e.g.  $S_{\text{hist}}$ ) from  
3572 historical and paleoclimate changes to the target  $S$  requires GCMs. For the historical period this  
3573 involves mainly how models capture gradients of sea surface temperature from the tropical Indo-  
3574 Pacific warm ocean to other regions, and their impact on cloud cover (section 4.2). There is  
3575 evidence that these gradients may have been stronger during cold, and weaker during warm  
3576 paleoclimates. The historical SST record meanwhile shows gradients within the tropics and mid-  
3577 latitudes strengthening more than predicted by GCMs. Stronger gradients are expected to increase  
3578 the (negative) global net cloud radiative effect (see section 3.4) for a given global mean  
3579 temperature.  
3580

3581 First, we consider the impact if this expected cloud sensitivity to warming patterns were wrong or  
3582 overestimated. Since the sensitivity causes us to infer  $S > S_{\text{hist}}$  because of the “warm-getting-  
3583 warmer” pattern in the historical record, an overestimated cloud sensitivity would imply an  
3584 overestimate of  $S$ . However during paleoclimate periods, where warm regions changed less than  
3585 cool regions, the same error could lead to an underestimate of  $S$ . We therefore find that co-  
3586 dependency between paleo and historical evidence is “buffered”. Co-dependencies are also  
3587 possible whereby errors in cloud physics more generally could affect both the historical transfer  
3588 function and process understanding; however, given that there are a wide range of cloud feedback  
3589 behavior and transfer functions implied across GCMs, a co-dependency should appear as a  
3590 correlation between the two, but available evidence does not suggest a correlation (Dong et al.,  
3591 2020) although this merits further investigation. So we conclude that uncertainty in the cloud  
3592 sensitivity to SST patterns is not an evident codependency concern.

3593  
3594 A more serious concern is misinterpretation of observed historical surface warming patterns and/or  
3595 incorrect expectations of forced patterns, which could affect historical and process evidence. The  
3596 calculations of the historical pattern effect (section 4.2.1) and low-cloud feedback (section 3.3.2)  
3597 both assume that long-term warming will be relatively uniform, as predicted by GCMs. However the  
3598 observed historical warming shows an increasing warm-cold gradient in the tropics which is not  
3599 fully predicted (section 4.2). The most likely explanations are an unforced variation,  
3600 underestimated lag effect of ocean thermal inertia, and/or response to volcanic forcing. Each of  
3601 these would be transient. However, there is evidence that a similar forced pattern could be missing  
3602 from GCMs due to mean-state biases (Kucharski et al., 2015), raising the possibility that the  
3603 residual historical warming is at least partly an equilibrium response to  $\text{CO}_2$  forcing (Luo et al.,  
3604 2018, McGregor et al., 2018). If so this would imply a negative feedback mechanism missing from  
3605 current GCMs and process evidence generally (section 3). It would also mean that  $S$  is closer to  
3606  $S_{\text{hist}}$ , i.e., not as high as calculated assuming the observed historical pattern to be unforced. This is  
3607 a reinforcing co-dependency which introduces a one-sided uncertainty into both the process and  
3608 historical evidence, addressed further below.

3609  
3610 **Aerosol forcing error.** Although better recognized with respect to the historical record, aerosol  
3611 forcing uncertainty also affects the paleo evidence. Given that different aerosol types are involved  
3612 during each era and may have different cloud impacts, it may be expected that any aerosol forcing  
3613 errors are unrelated, in which case no co-dependency is expected. But to consider this possibility  
3614 anyway, if present-day anthropogenic aerosol negative forcing were weak relative to expectations,  
3615  $S$  would be underestimated from historical evidence. However, since the LGM was much dustier  
3616 than the Holocene, a related situation for dust forcing would cause us to overestimate  $S$  from paleo  
3617 evidence. Hence, even if the errors were related they would tend to compensate if the two  
3618 estimates are combined (referred to here as “buffering”). If instead pre-industrial aerosol amounts  
3619 are underestimated then our historical-estimated  $S$  would be too high, yet with less vegetation-  
3620 related aerosol during the sparsely vegetated LGM our paleo-estimated  $S$  would be too low. Thus,  
3621 the errors will again tend to compensate if the two are combined.

3622  
3623 Due to the complexity of aerosols and their effects, one cannot be sure about buffering. Therefore,  
3624 we have done calculations (section 6.3 below) of the impact of co-dependency for extreme cases  
3625 of fully co-dependent, vs. anti-dependent, effects. This follows the methodology of Annan and  
3626 Hargreaves (2017), but uses a more appropriate two-layer climate model for the historical period.  
3627 We find that the posterior PDF is only modestly affected even in these extreme cases. We thus  
3628 conclude that it is safe to set aside major concerns about co-dependency of the aerosol  
3629 uncertainties.



3630  
3631 **CO<sub>2</sub> radiative forcing error.** There is some uncertainty in the radiative forcing per doubling of  
3632 CO<sub>2</sub>,  $\Delta F_{2\times\text{CO}_2}$  (section 3.2.1). If  $\Delta F_{2\times\text{CO}_2}$  is higher than the best estimate, then the true  $S$  will  
3633 be proportionately higher, since all process evidence is referenced to radiative flux variations  
3634 rather than CO<sub>2</sub> changes, while  $S$  is defined based on CO<sub>2</sub> change. For other lines of evidence, an  
3635 impact is also expected but it depends on the relative magnitude and direction of the CO<sub>2</sub> vs. non-  
3636 CO<sub>2</sub> forcings, since the contribution of CO<sub>2</sub> increases with  $\Delta F_{2\times\text{CO}_2}$ : for historical warming (where  
3637 CO<sub>2</sub> and non-CO<sub>2</sub> forcings oppose each other) a high  $\Delta F_{2\times\text{CO}_2}$  would push net forcing higher, thus  
3638 historical-estimated  $S$  lower, while for prehistoric changes (where other forcings reinforce CO<sub>2</sub>) this  
3639 would push paleo-estimated  $S$  higher. Because of the buffering of effects between the historical  
3640 and paleo periods, and since the uncertainty in CO<sub>2</sub> forcing is relatively small, we ignore this  
3641 codependency.

3642  
3643 It could be argued that the above scenarios only deal with uncertainties we know about, but that  
3644 some major oversight, invisible phenomenon, or structural error in how the problem is formulated  
3645 could also affect multiple lines of evidence. It is however difficult to deal with such “unknown  
3646 unknowns” without concrete proposals for particular problems whose possible impacts can be  
3647 explored rationally. In trying to consider plausible candidates on the process side—very strong and  
3648 unanticipated feedback from low or high clouds being the only candidates that seem physically  
3649 able to deliver large feedbacks—it is difficult to see how a strong feedback would fail to have  
3650 registered in either of the other lines of evidence, unless some second, unrelated surprise  
3651 coincidentally canceled it out. Such multiple surprises are already catered for by considering the  
3652 evidence to be independent, as long as each surprise has been allowed for properly via the tails in  
3653 the respective likelihoods (see also section 7.3). Possible medium-term Earth-system responses,  
3654 such as a forest dieback, could fail to register in either historical or process understanding, but  
3655 would not appear to deliver a large enough feedback for this dependency to significantly affect  
3656 matters. Very slow responses and non-linearities would affect only the paleo evidence and were  
3657 accounted for there.  
3658

## 3659 **6.3 Simple dependence test**

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3661 Since we did find a possible reinforcing co-dependency between the process and historical  
3662 evidence associated with the pattern effect, we modelled its effect using a simplified calculation in  
3663 which the historical and process likelihoods vs.  $\lambda$  are approximated as Gaussians that each include  
3664 a distinct, unshared error component, and a shared error component from the pattern effect. We  
3665 suppose here that half the variance in historical  $\Delta\lambda$  ( $0.3^2$  from section 4) arises from uncertainty in  
3666 the forced SST pattern, which would also affect the evolution of cloud feedbacks; the other half is  
3667 from uncertainty in the radiative response to a known pattern (accounted for separately in the  
3668 process analysis). This leads to a shared error component of  $N(0, 0.21)$ . The baseline process  
3669 distribution,  $N(-1.30, 0.44)$  from Table 1, therefore includes this plus an unshared component  
3670  $N(-1.30, 0.39)$  and the historical likelihood, approximated as  $N(-1.07, 0.55)$ , includes this plus an  
3671 unshared component  $N(-1.07, 0.51)$ . The two total  $\lambda$  likelihoods can be combined either assuming  
3672 them to be independent, or assuming the unshared components to be independent but the  
3673 corrections to be duplicated. The PDF of  $S$  (based on the process and historical evidence only)  
3674 has a 90% range of 2.2-6.9 K in the first case, widening to 2.1-7.4 K in the second case. In other  
3675 words, the co-dependency has a fairly small effect on the final result, at least if approached in this  
3676 way. The basic reason for this is that the shared error variance,  $0.04 \text{ (W m}^{-2} \text{ K}^{-1})^2$ , is six times

3677 smaller than that of the unshared historical error and three times smaller than that of the unshared  
3678 process error. Therefore the pooled uncertainty is dominated by the unshared components.  
3679 Nonetheless this dependency may deserve further attention especially if other uncertainties (e.g.,  
3680 in aerosol forcing) are significantly narrowed.  
3681

## 3682 **6.4 Summary**

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3684 We judge that for the most part, the three lines of evidence appear to be practically independent in  
3685 the sense that any significant errors we can envisage would affect the lines differently. We do  
3686 however find one important uncertainty for which this is not the case, related to “pattern effects.” If  
3687 CO<sub>2</sub> forcing happens to produce more warm-region warming than expected, this would potentially  
3688 affect both historical and process-based estimates of  $S$  in the same sense. Idealized calculations  
3689 (section 6.3) indicate that allowing even for this relatively strong co-dependency does not strongly  
3690 affect a combined PDF. In our subsequent analysis we will therefore proceed with a baseline  
3691 approach of considering the three main lines of evidence to be independent. However, given that  
3692 the possibility of major, unexpected dependencies can never be ruled out, we also explore  
3693 possible impacts of this using more drastic tests where single lines of evidence are discarded  
3694 altogether (section 7.3).  
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# 7. Quantitative Synthesis of Evidence for S

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Here we present results from the Bayesian approach described in section 2 to produce quantitative estimates of the probability distribution for  $S$  given the evidence presented in the previous sections. This builds on many previous studies (e.g., Annan and Hargreaves, 2006, Hegerl et al., 2006; Stevens et al., 2016).

First, we present the results of a “Baseline” calculation. This calculation is the synthesis of our basic assumptions as outlined in the previous sections, and is not primarily intended to represent a best or consensus estimate. It is, however, based on transparent assumptions, the sensitivity to which can be tested in a relatively straightforward way. In following sections we assess the sensitivity of the Baseline outcome to (a) the choice of prior, (b) the exclusion of each of the lines of evidence in turn and (c) allowances for potential uncertainties not explicitly catered for elsewhere in our calculations. These tests respectively explore: (a) the robustness of our results to alternative formulations of prior beliefs as represented in the Bayesian approach; (b) the influence of the different lines of evidence and how much of a constraint may be provided with only two independent lines; and (c) how much additional uncertainty a researcher would have to have in order for their uncertainty to significantly influence the results. These sensitivity tests inform the interpretation of our results in section 8, based in part on the ‘storylines’ approach of Stevens et al. (2016) (SSBW16).

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## 7.1. Baseline calculation

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Figure 20 shows our Baseline calculation of the posterior PDF for  $S$ , and how the lines of evidence contribute to it. The PDF for  $S$  is calculated by sampling from a uniform prior on feedback components and performing a Bayesian update using evidence likelihoods from individual feedback components (section 3), historical evidence (section 4) and evidence from warm and cold paleoclimates (section 5). The Emergent Constraint evidence from section 3 is not included in the Baseline calculation. Likelihood weights for each line of evidence are multiplied, based on the assumption that the lines of evidence are independent (see section 2 for details). The 66% (17-83%) range for  $S$ , given all lines of evidence included, is 2.6-3.9 K with a median of 3.1 K. The 90% (5-95%) range is 2.3-4.7 K.

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Figure 20 b shows marginal likelihood functions for  $S$  from the various lines of evidence. The process likelihood depends on the prior (section 2), and is calculated using the default uniform  $\lambda$  prior used for the Baseline calculation. These likelihoods give one indication of the relative effectiveness of the various lines of evidence in constraining  $S$ . The values of these likelihoods at the vertical grey lines indicate the relative strength of the corresponding evidence in constraining the 17th and 83rd percentile values (66% range) of the posterior PDF of  $S$ , with a smaller likelihood indicating a stronger constraint. The strongest constraint at the upper end of the  $S$  range arises from the paleoclimate evidence (mainly due to that from cold climates), with a weaker constraint from the process evidence and the weakest constraint arising from the historical evidence. The strongest constraint at the lower end of the range arises from the historical

3742 evidence, with the process evidence and warm paleoclimate evidence giving weaker  
3743 constraints, and the cold paleoclimate evidence providing the weakest constraint.

3744  
3745 A limitation of comparing marginal likelihoods as above is that, unlike the historical and paleo  
3746 evidence, the process evidence (based on feedback components) cannot be uniquely expressed  
3747 as a function of  $\lambda$  and  $\Delta F_{2\times\text{CO}_2}$  (see section 2). This makes the marginal likelihood dependent on  
3748 the Bayesian prior on the individual feedback variables. An alternative approach is to compare the  
3749 predicted PDF of  $S$  based on the process understanding combined with a uniform  $\lambda$  prior with the  
3750 marginal likelihoods of the historical and paleo evidence (cf. eq. 10); this is done in Fig. 20 a  
3751 (note that for plotting consistency the historical and paleo evidence is shown as PDFs under  
3752 uniform- $S$  priors, preserving the shape of the likelihoods).

3753  
3754 Multiple PDFs (or likelihoods) based on different sources of information are not necessarily  
3755 expected to match, only to overlap. In our case there is substantial overlap between the lines of  
3756 evidence, whether regarded in terms of likelihood functions (Fig. 20 b) or PDFs obtained as in  
3757 Fig. 20 a, and maximum likelihood values are all fairly close. This indicates strong consistency  
3758 among the three lines of evidence. The tails of the likelihoods and PDFs are different, however,  
3759 which indicates variation in the strength of the constraints.

3760  
3761 Our Baseline calculation above is based on one particular prior, assumes independence between  
3762 lines of evidence, and makes no allowances for ‘unknown unknowns.’ We therefore perform a  
3763 number of sensitivity tests to explore these limitations, to allow for the possibility that our Baseline  
3764 range for  $S$  is over confident.

## 3765 **7.2. Sensitivity to priors**

3766  
3767 We now consider different prior distributions, and discuss the alternative perspectives that these  
3768 priors may represent.

3769  
3770 As discussed in section 2, we place priors on all independent variables of our inference model,  
3771 including the six feedbacks  $\lambda_i$ , and these induce a prior predictive distribution (PPD) on each  
3772 dependent variable including  $S$ . The PPD of  $S$  indicates what its posterior PDF would be, given the  
3773 inference model and priors, before any subsequent updating with evidence likelihoods. As such,  
3774 the PPD for  $S$  can be a useful tool for understanding the influence of the prior on the predicted  
3775 variables for a given inference model.

3776  
3777 Our Baseline calculation places independent, uniform priors on the  $\lambda_i$  feedbacks, as is implicitly  
3778 assumed in many past studies of these feedbacks (section 2.4.3). Although we use uniform priors  
3779 on  $\lambda_i$ , other broad functions of  $\lambda_i$  yield similar results as long as the feedback priors are  
3780 independent. A prior with unbounded uniformly distributed  $\lambda_i$  feedbacks induces a PPD for  $\lambda$  which  
3781 is also unbounded and uniformly distributed (hence will be called ‘UL’). This, given a reasonably  
3782 well-constrained value for  $\Delta F_{2\times\text{CO}_2}$ , results in a PPD for  $S$  that decreases with increasing  $S$  (Figure  
3783 21 b), because smaller and smaller changes in  $\lambda$  change  $S$  by a given amount as  $\lambda$  approaches  
3784 zero and  $S$  becomes large (Roe and Baker, 2007; Frame et al., 2005). (Note however that for  
3785 practical reasons we place bounds on the  $\lambda_i$  feedback priors in our numerical calculations—see  
3786 section 2.4.4).

3787

3788 It may be argued that a uniform  $\lambda$  prior is undesirable since it assigns low probability density in the  
3789 PPD for  $S$  at high values of  $S$  from the outset, and it has been argued in previous studies (e.g.,  
3790 Frame et al., 2005) that a state of ignorance about  $S$  is represented by considering a uniform prior  
3791 probability density of  $S$  (see section 4). Therefore we also consider an alternative prior that induces  
3792 an approximately uniform PPD on  $S$ , which we refer to as the uniform  $S$  prior (US) for brevity.  
3793

3794 Specifying a prior that is uniform in  $S$  is not straightforward in our inference model. There is no  
3795 unique way to choose priors on the feedbacks  $\lambda_i$  to yield any given PPD for  $S$ ; there are many  
3796 possible joint feedback priors that yield a uniform PPD for  $S$  over some interval. Different such joint  
3797 priors over  $\lambda_i$  can induce different posterior PDFs on  $S$ , even though their induced PPD( $S$ ) is the  
3798 same. The specific case of a uniform PPD on  $S$  implies that the feedbacks have a high probability  
3799 of summing to a relatively small value. Accordingly, any US prior must possess at least one of two  
3800 characteristics: it must either assume the uncertainties in the feedbacks to be anti-correlated, or  
3801 else assume that the individual feedbacks are likely to take extremely small values. In the former  
3802 case, the feedbacks are likely to have a small sum because of a natural tendency to oppose one  
3803 another; in the latter case, because sufficiently small feedbacks will have a small sum. Although  
3804 we experimented with both types of prior, we judged the latter, small-feedback type to be  
3805 unacceptable because it would assign an extremely small prior probability to the most likely values  
3806 of some of the feedback components (e.g., Planck, see section 3). We therefore limit further  
3807 consideration to US priors achieved by feedback anticorrelation.  
3808

3809 To construct a prior with a uniform PPD for  $S$  using the full inference model, we take the sample  
3810 from the Baseline UL prior and weight each sample instance according to its predictive value for  $S$   
3811 in order to give a uniform PPD for  $S$  (see section 2.3). This approach is similar to that followed by  
3812 Aldrin et al. (2012) to construct a uniform prior for  $S$  when using an inference model with priors on  
3813 multiple variables. Recalculation of the posterior PDF of  $S$  from all evidence using this prior gives  
3814 a 66% range of 2.8-4.5 K (Table 10 ). This shows that our final result with all evidence is  
3815 encouragingly stable to changes in prior; even with this quite drastic change in the prior and  
3816 corresponding PPD for  $S$ , the posterior PDF of  $S$  only changes by 0.2 K at the lower end and 0.6 K  
3817 at the upper end of the 66% range. While other priors could be considered, the UL and US priors  
3818 appear to span the range of reasonable options for broad priors.  
3819

3820 This US prior does however have characteristics that some may find hard to justify. It requires  
3821 abandoning the presumption that feedbacks are *a priori* independent, instead assuming they are  
3822 anti-correlated or naturally compensate (in our prior sample, the prior correlation of any one  $\lambda_i$   
3823 component with the sum of the other five is  $-0.83$  ). While some feedbacks do indeed negatively  
3824 correlate (for example water vapor and lapse rate, see section 3.2.3), discovering this for some  
3825 feedbacks through process knowledge and evidence is not the same as assuming it beforehand  
3826 for all feedbacks. Doing so would imply that if knowledge is gained about one feedback (say, ice  
3827 albedo), one's confidence in the other feedbacks (e.g., clouds) will automatically improve and best  
3828 estimates possibly shift, even though nothing was directly observed about the others, and we have  
3829 no evidence for such a link. It would also imply that uncertainty could become smaller when  
3830 feedbacks are summed, rather than larger as would normally be the case. There is no evident *a*  
3831 *priori* rationale for preferring this negative (compensating) correlation over a positive (reinforcing)  
3832 one—and allowing for a broad range of possible correlations of both directions and averaging the  
3833 results would produce an outcome very close to that with no correlation (our Baseline UL prior).  
3834 Previous work on feedbacks or using climate models has never, to our knowledge, treated  
3835 evidence in this way.  
3836

3837 Note that our priors on  $\lambda_i$  feedbacks should not be considered comparable to priors used in  
3838 Bayesian studies (e.g., Johansson et al., 2015; Skeie et al., 2014, and others discussed in section  
3839 4) that do not explicitly consider individual feedback processes as evidence, and which take  $S$  or  $\lambda$   
3840 as an independent variable, rather than  $\lambda_i$  which are the independent variables used here. In our  
3841 inference model, the process information and prior together play the same role as would the prior  
3842 in any study not treating process information about individual feedbacks as evidence (cf. eq.  
3843 10), and a good deal of this information is not new (e.g., the Planck response and lapse-rate/water-  
3844 vapor feedbacks). Therefore such studies would in principle be expected to include some of our  
3845 process evidence in their prior, which should be considered if comparing assumptions here to  
3846 those used elsewhere.

### 3847 **7.3 Sensitivity to specification of evidence**

3848  
3849 Here we test the sensitivity of our calculations to modifying the evidence as encoded in our  
3850 likelihood functions for  $S$ . First, we exclude each line of evidence in turn from the Baseline  
3851 calculation. These ‘leave-one-out’ calculations give an indication of the relative effectiveness of  
3852 the various lines of evidence in constraining  $S$ . Although we compared marginal likelihoods and  
3853 PDFs from individual lines of evidence compared with priors in section 7.1, the sensitivity tests  
3854 shown here may be considered more relevant to identifying the impacts of individual lines of  
3855 evidence on the posterior PDF in a context where the majority of evidence is being applied. The  
3856 results are summarized in Table 10 and Figure 22 (see UL No Process, UL No Historical,  
3857 UL No Paleo Warm and UL No Paleo Cold). Comparing the results of the different leave-one-out  
3858 tests confirms the relative strengths of the constraints of the individual lines of evidence on the  
3859 upper and lower bounds for  $S$  reported in section 7.1 (see Figure 20 ).

3860  
3861 We also show the impact of removing the process evidence under a uniform Prior for  $S$  (US No  
3862 Process). This mimics some past studies that did not use process understanding and expressed a  
3863 uniform prior on  $S$ ; it therefore considers the situation where one views the process understanding  
3864 (including a UL prior and the structural understanding of eq. ( 5) as a process model replacing a  
3865 uniform- $S$  prior (see US No Process BU, Table 7.1, Figure 22 ; and Fig. 20 b). This results in  
3866 higher sensitivities than UL No Process BU, such that if one considers the removal of this process  
3867 model and replacement with uniform- $S$ , the process model is found to exert a stronger constraint at  
3868 the high end but less at the low end, compared to the conclusions if one discards only the process  
3869 evidence but still maintains a consistent UL prior.

3870  
3871 In addition we explore the possibility that our Baseline range for  $S$  may be over-confident due to  
3872 limitations in our treatment of the various lines of evidence. The Bayesian approach is by its very  
3873 nature subjective, and our inference model (or some other analysis choice) may have limitations  
3874 that potentially result in over-confident predictions. Other researchers may make different  
3875 assumptions, and we would like to explore what range of results are at the edges of what we think  
3876 plausible. Hence we use sensitivity tests to explore the consequences of possible alternative  
3877 assumptions. For further discussion of the limitations of our approach, see section 7.5 below.

3878  
3879 First we revisit the ‘leave-one-out’ calculations, which may also be considered as worst-case  
3880 explorations of what our results would look like if a line of evidence were for some reason  
3881 substantially compromised, or not accepted by some readers, or highly co-dependent with another  
3882 evidence line in some way unrecognized in our analysis. As such these can be used to place

3883 generous upper bounds on the impacts of uncertainties in individual lines of evidence on our  
3884 posterior PDF for  $S$ .

3885  
3886 Excluding the process evidence from the Baseline calculation increases the 66% posterior range  
3887 for  $S$  from 2.6-3.9 K to 2.4-4.1 K, and the 5-95% range from 2.3-4.7 K to 2.0-5.2 K. Excluding the  
3888 process evidence from the calculation with the uniform  $S$  prior has a larger effect, increasing the  
3889 66% and 5-95% ranges to 2.8-5.2 K and 2.3-6.9 K respectively. Hence the upper tail of the  
3890 distribution is not robustly constrained by historical and paleoclimate information combined alone,  
3891 as the resulting constraint depends strongly on the prior. Nevertheless, even then sensitivities  
3892 beyond 5.9 K are estimated to have < 10% probability, yielding a similar upper bound to the IPCC  
3893 AR5 assessment, which estimated the probability of sensitivities above 6 K as ‘very unlikely’, i.e.  
3894 <10%.

3895  
3896 These are very extreme sensitivity tests; for them to be considered reasonable, new evidence  
3897 would need to come to light that would justify complete dismissal of all of the multiple elements of  
3898 the process evidence (and hence much of our physical understanding of the climate system).  
3899 Since this is a very extreme scenario, we do not consider the ‘No-Process’ case to plausibly  
3900 represent the overall structural uncertainty. The strong sensitivity to removing the Process  
3901 evidence illustrates how important this line of evidence is to constraining the upper bounds on  $S$ ,  
3902 under a uniform- $S$  prior.

3903  
3904 The other leave-one-out tests may be considered less extreme in that they gauge the impact of  
3905 excluding individual sets of observations (historical, warm and cold paleoclimate) from the Baseline  
3906 calculation for  $S$ . Excluding these lines of evidence from the Baseline calculation individually  
3907 reduces the 5th percentile by at most 0.3 K, to 2.0 K, and increases the 95th percentile value by at  
3908 most 0.4 K, to 5.1 K. Although we consider it extremely unlikely that new information could ever  
3909 lead a future assessment to dismiss an entire line of evidence, it is conceivable that multiple lines  
3910 of evidence (including the process evidence) could weaken or be interdependent to a level which  
3911 has a similar-order effect on the range of  $S$  to the above (see Figure 24 ). The leave-one-out  
3912 tests also place a generous upper bound on the effects of dependencies between any two lines of  
3913 evidence, given that removing one line of evidence in a pair will remove the effect of dependencies  
3914 between that pair but also removes the independent contribution of that line of evidence.

3915  
3916 The Baseline calculation does not include any evidence arising from emergent constraints based  
3917 upon present-day climate observations (see discussion in section 3.6). In addition to the above  
3918 sensitivity tests, we test the impact of adding this line of evidence to the Baseline calculation (see  
3919 UL + Emergent Constraints in Table 10 and Figure 21 ). This shifts the 66% range from 2.6-  
3920 3.9 K to 2.7-4.0 K and the 5-95% range from 2.3-4.7 K to 2.4-4.8 K. The shift upward of 0.1 K is  
3921 consistent with the higher  $S$  suggested by this evidence, and demonstrates the potential for future  
3922 revisions to our assessment of the evidence to improve our estimate of  $S$ . However its impact is  
3923 small, and is bounded by the selected leave-one-out tests above. This reflects the relatively low  
3924 confidence placed in this line of evidence and the fact that its maximum-likelihood  $S$  is not far from  
3925 that of the other evidence.

3926  
3927 Another potential limitation of our approach is that we assume Gaussian distributions for many  
3928 prior expert PDFs on independent variables. This does not allow for uncertainty in the assigned  
3929 means and standard deviations themselves. Accounting for this uncertainty by sampling from a  
3930 distribution of candidate standard deviation values would lead to a distribution with more kurtosis,  
3931 i.e., fatter tails. Another way of looking at this is that Gaussians may express overconfidence in our

3932 ability to dismiss surprising values far from the most likely one, and may therefore not well  
3933 represent fully informed beliefs that are appropriately aware of structural uncertainty. To address  
3934 this concern we include an additional sensitivity test in which we replace many of the Gaussian  
3935 evidence distributions with Student's  $t$ -distributions with five degrees of freedom. (A  $t$ -distribution  
3936 formally results if the Gaussian parameters are being estimated empirically from a finite, unbiased  
3937 sample, see Gelman et al., 2013; although our distributions are arguably better viewed as expert  
3938 judgments, the  $t$ -distribution is still a useful generalization for our purposes). We perform this  
3939 replacement for variables where small samples, structural uncertainty or possible unrecognized  
3940 factors could be a significant concern. The choice of five degrees of freedom is motivated by the  
3941 historical pattern effect correction term  $\Delta\lambda$ , which is informed by the sample mean and standard  
3942 deviation of six GCM experiments. This is represented by the Gaussian  $N(-0.5, 0.3)$  in the Baseline  
3943 calculation. In our sensitivity test we replace this with a  $t$ -distribution with five degrees of freedom  
3944 and mean and scale parameters equal to the mean and standard deviation of the Gaussian  
3945 distribution respectively. This increases the standard deviation by 30% from 0.3 to 0.39. The  
3946 resulting distribution has a 66% range of  $[-0.82, -0.18]$  which is very similar to that for the  
3947 Gaussian distribution ( $[-0.79, -0.21]$ ), but has a 5-95% range of  $[-1.1, +0.1]$  which is 22% wider  
3948 than that from the Gaussian distribution ( $[-0.99, -0.01]$ ). We apply the same procedure to fatten the  
3949 tails of the following other independent variables: the process evidence feedback likelihoods  $\lambda_i$ , the  
3950 adjusted forcing  $\Delta F$  and state-dependence correction factor  $\alpha$  for the paleoclimate cold periods, the  
3951  $\text{CO}_2$  concentration and slow-feedback scaling  $f_{\text{ESS}}$  for the paleoclimate warm periods, and the ratio  
3952  $(1+\zeta)$  of ECS to  $S$ . In each case the  $t$ -distribution gives a very similar 66% range to that of the  
3953 Gaussian distribution it replaces. We find that substituting these fat-tailed distributions for all of the  
3954 above into the Baseline calculation increases the width of the 66% range for  $S$  slightly from 2.6-3.9  
3955 K to 2.5-4.0 K, and increases the width of the 5-95% range a little more, from 2.3-4.7 K to 2.2-4.9  
3956 K. These wider ranges are already encompassed by our other plausible sensitivity tests described  
3957 above, indicating that our conclusions on the bounds of both ranges for  $S$  are reasonably robust to  
3958 structural uncertainty.

## 3959 **7.4 Implications for related sensitivity measures and** 3960 **future warming**

3961 Here we present results showing how  $S$  and its PDF map onto a few other related quantities of  
3962 interest. To relate these we must rely entirely on GCMs, which can predict  $S$  and the other  
3963 quantities.  
3964

3965  
3966 Via eq. ( 8) and the PDF on  $\zeta$  given in section 5.2.3, our calculation provides a simultaneous  
3967 calculation of the posterior PDF of ECS, which may be compared with that of  $S$ . For our Baseline  
3968 case the 5-95% (2.2-4.9 K) and 66% (2.6-4.1 K) ranges of ECS (Table 7.2) are slightly wider and  
3969 stretched higher than those for  $S$  (2.3-4.7 K and 2.6-3.9 K respectively). This is as expected from  
3970 the comparison shown in Fig. 1 and resulting distribution of  $\zeta$ . There is only a modest increase  
3971 in the widths of the ECS PDFs compared to those for  $S$ , presumably because the paleo evidence  
3972 more directly constrains ECS, while other evidence more directly constrains  $S$ . Under our uniform-  
3973  $S$  prior, however, the 66% range for ECS (2.7-4.6 K) expands slightly compared to that for  $S$  (2.8-  
3974 4.5 K) but does not shift upward, while the 5-95% range for ECS (2.3-5.6 K) is shifted slightly  
3975 towards lower values than for  $S$  (2.4-5.7 K) This counterintuitive result may be due to the *a priori*  
3976 correlation structure implicitly required to reconcile the physical model (section 2.2) with a uniform  
3977 prior probability of  $S$ : because  $\zeta$  is uncertain, the strong expectation for high  $S$  expressed by this  
3978 prior (compared to that of the Baseline prior) combined with the evidentiary constraints against



3979 high  $S$ , implies that *a posteriori*  $\zeta$  has a strong chance to be negative even though *a priori* it was  
3980 expected to be positive on average (remembering that, in a Bayesian analysis, the PDFs of all  
3981 variables are updated when evidence is considered). Because of this, the bounds from reasonable  
3982 sensitivity tests we obtain for ECS are slightly smaller than those for  $S$ .

3983  
3984 For other quantities (TCR and future warming), we obtained approximate PDFs from their fits to  $S$ ,  
3985 broadened according to the sample spread about this fit. These fits were shown in Fig. 1; the  
3986 resulting PDFs of warming are shown in Fig. 23 for the Baseline case, and ranges are given in  
3987 Table 11 for other cases. As the relationship between the different climate sensitivity measures  
3988 is not well understood (e.g., AR4 Fig. 10.15; Frey et al., 2017; Grose et al., 2018), we choose  
3989 linear fits. These linear fits do not extrapolate through the origin for non-equilibrium scenarios, but  
3990 this is expected, as the fraction of warming that remains unrealized (at the end of century in the  
3991 case of the RCP's, or time of doubling in the case of TCR) will vary with  $S$ . Within the range of  
3992 substantial probability of  $S$ , the relationships do not show any robust nonlinearity, so none is  
3993 accounted for.

3994  
3995 The 66% range we find for TCR (1.5–2.2 K in the Baseline calculation, and up to 2.4 K otherwise)  
3996 is much narrower than the IPCC AR5 likely range of 1.0–2.5 K. However our assessment of this  
3997 quantity is very limited and should be treated with considerable caution, as it comes largely from  
3998 sources of information more relevant to  $S$  (paleoclimate and atmospheric process evidence) which  
3999 is then converted to TCR using coupled climate models from AR5, rather than a bottom-up  
4000 assessment of TCR that properly accounts for our physical understanding, uncertainties in  
4001 transient processes (in particular, ocean processes), and historical changes on shorter time  
4002 horizons of greater relevance to TCR. A more thorough assessment of TCR is set aside for future  
4003 projects.

4004  
4005 For the Baseline case shown, the future-warming PDFs indicate that the probability that warming  
4006 relative to 1995 will exceed 1.4 K (roughly equivalent to 2 K above pre-industrial, Hawkins et al.  
4007 2017) by late this century is 17% under RCP2.6, 83% under RCP4.5, 92% under RCP6.0 and  
4008 >99% under RCP8.5. Note that while RCP8.5 has sometimes been presented as a “business as  
4009 usual” scenario, it is better viewed as a worst case (e.g., Hausfather and Peters, 2020). We make  
4010 no claims here on scenario probabilities, only on warming probabilities conditional on a broad  
4011 range of possible scenarios.

4012  
4013

## 4014 **7.5 Limitations, caveats and potential future** 4015 **approaches**

4016  
4017 Our assessment has taken an ambitious approach which has for the first time attempted to model  
4018 the relationships between diverse lines of evidence (including feedback components and pattern  
4019 effects) with  $S$  in a consistent overarching inference model framework. This approach like any  
4020 other has its potential limitations, which will only become clearer in future work which develops the  
4021 approach. Here we discuss various limitations of the statistical approach outlined here that could  
4022 potentially be improved in future work.

4023

4024 First, in each section we have made those choices which we consider the most defensible, and  
4025 carried a single likelihood function for each line of evidence forward into the synthesis calculations.  
4026 In future work it could be possible to develop a range of plausible alternative likelihoods for each

4027 line of evidence and apply these as sensitivity tests in the synthesis. While we have tested the  
4028 effect of substituting symmetric fatter-tailed distributions for Gaussian distributions, future studies  
4029 could test the sensitivity to other changes, for example, skewed distributions. The statistical  
4030 models developed here are intended to codify the existing knowledge from the literature. Future  
4031 research should develop these models and it is quite likely that they may be re-parameterized and  
4032 may even be formulated in terms of other variables.  
4033

4034 Our treatment of possible dependencies across evidence lines was limited to use of  $\Delta F_{2xCO_2}$   
4035 throughout and some sensitivity tests around pattern effect dependence. Treatments for  
4036 dependencies are best addressed by modelling them directly within the inference model. This  
4037 could be taken further in future work, for instance by explicitly building in additional dependencies  
4038 between feedback components, forcings and feedbacks, or other quantities for which there is  
4039 evidence of dependence (e.g., see Annan and Hargreaves, 2017). In particular dependencies  
4040 arising from pattern effects could be modelled more carefully once better understood, and other  
4041 dependencies (including “buffered” ones) could be modelled. The dependence between forcing  
4042 and feedbacks remains poorly understood (section 3.4), and better understanding might suggest a  
4043 different approach to that taken here, although we don’t expect this to significantly affect results.  
4044

4045 Zelinka et al. (2020) show that the range in  $S$  increases from 2.1-4.7 K in CMIP5 to 1.8-5.6 K in  
4046 CMIP6. This demonstrates the importance of combining multiple lines of evidence, as GCMs alone  
4047 are not producing increasingly confident estimates. We have deliberately not used the range of  $S$   
4048 values from climate models to directly inform our likelihoods, but climate models inevitably inform  
4049 our estimates, for example in the estimation of the pattern effect term in the historical likelihood,  
4050 some of the feedback subcomponents from the process evidence, and some of the paleo radiative  
4051 forcing estimates (see section 6.2). We have incorporated some new results from CMIP6, but  
4052 results from CMIP6 models on the strength of the pattern effect are not yet fully available. It is in  
4053 principle possible that our results could change, for example if new models predicted radically  
4054 different pattern effects, which could change our interpretation of evidence from the historical  
4055 period, or different feedbacks which are not strongly constrained by other evidence. However, any  
4056 change in the range of  $S$  from a synthesis of all lines of evidence would be expected to be smaller  
4057 than the change in the model range alone.  
4058

4059 Finally, there are other possible choices that could be made for the synthesis methodology, or in  
4060 the use of alternative lines of evidence, and sometimes our reasons for choosing one over another  
4061 are based on very subjective judgements. Some of the difficult issues (arising around the  
4062 specifications of the priors for example) could potentially be addressed in future using statistical  
4063 simulation approaches.  
4064

## 4065 **7.6 Summary**

4066 Our Baseline calculation gives a 66% (17-83%) range for  $S$  of 2.6-3.9 K, and a 5-95% range of 2.3-  
4067 4.7 K (grey line, Figure 24 ). This case includes all evidence considered in this report, except  
4068 the “emergent constraint” evidence, whose independence from other evidence is uncertain (section  
4069 3.6). We consider the sensitivity tests where we individually remove the historical, cold or warm  
4070 paleoclimate evidence to bound any changes to these ranges that could plausibly occur due to  
4071 reasonable alternative interpretations of the evidence (see orange and blue lines on Figure 24 ).  
4072 These place bounds of 2.3 K and 4.1 K on the 66% range and 2.0 K and 5.1 K on the 5-95% range  
4073

4074 for  $S$ . If we additionally include a sensitivity test where we substitute a uniform  $S$  prior into the  
4075 Baseline calculation, we obtain bounds of 2.3 and 4.5 K on the 66% range (see magenta line,  
4076 Figure 24 ) and 2.0 and 5.7 K on the 5-95% range for  $S$ . Modifying the baseline calculation to  
4077 include the emergent constraint evidence or to assume fat tailed-distributions results in ranges  
4078 which are bounded by the above.

4079  
4080 All of our plausible alternate calculations for the PDF of  $S$  suggest a considerable narrowing of the  
4081 range compared to that assessed at the time of the AR5 (cyan line, Figure 24 ). This remains  
4082 true for the equilibrium climate sensitivity (ECS). A weaker constraint would be found if we  
4083 disregarded all process evidence, since in that case the resulting combined paleo and historical  
4084 PDF would be highly sensitive to prior information in the upper tail. Yet even the most generous  
4085 allowances for uncertainty result in a stronger constraint on  $S$  than that which was available at the  
4086 time of the AR5 assessment, indicating an advance in our assessment of the evidence for  $S$ . This  
4087 increased constraint comes almost entirely from bringing up the low end, rather than reducing the  
4088 high end.

## 4090 8. Summary and Conclusions

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### 4092 8.1 Considerations

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The objective of this work was to analyze all important evidence relevant to climate sensitivity, and use that evidence to draw conclusions about the probabilities of various values of the sensitivity. In so doing we have examined the interdependence of different lines of evidence and the possibility that structural or other flaws in our understanding might affect conclusions or lead to overconfidence. There are subjective elements to such an exercise, but there are also objective ones—in particular, enforcing mathematical rules of probability to ensure that our beliefs about climate sensitivity are internally consistent and consistent with our beliefs about the individual pieces of evidence.

All observational evidence must be interpreted using some type of model that relates underlying quantities to observables, hence there is no such thing as a purely observational estimate of climate sensitivity. Uncertainty associated with any evidence therefore comes from three sources: observational uncertainty, potential model error, and unknown influences on the evidence such as unpredictable variability (which may or may not be accounted for in one's model). By comparing past studies that used different models for interpreting similar evidence (see e.g., section 4.1), we find that the additional uncertainty associated with the model itself is considerable compared with the stated uncertainties typically obtained in such studies assuming one particular model. When numerical global climate models (GCMs) are used to interpret evidence, they reveal deficiencies in the much simpler models used traditionally—in particular the failure of these models to adequately account for the effects of inhomogeneous warming. This insight is particularly important for the historical temperature record (section 4.2), which is revealed by GCMs to be compatible with higher climate sensitivities than previously inferred using simple models. In general, many published studies appear to have overestimated the ability of a particular line of evidence to constrain sensitivity, sometimes leading to contradictory conclusions (see section 4.1). When additional uncertainties are accounted for, single lines of evidence can sometimes offer only relatively weak constraints on the sensitivity.

The effective sensitivity  $S$  analyzed here is defined based on the behavior during the first 150 years after a step change in forcing, which is chosen for several practical reasons explained in section 2.1. While our study also addresses other measures of sensitivity (the Transient Climate Response TCR and long-term equilibrium sensitivity), the calculations of these were not optimal and future studies could apply a methodology similar to that used here to quantify them, or other quantities perhaps more relevant to medium-term warming, more rigorously.

After extensively examining the evidence qualitatively and quantitatively (sections 3-5), we followed a number of past studies and used Bayesian methods to attempt to quantify the implications and probability distribution function (PDF) for  $S$ . It must be remembered that every step of this process (choosing priors, computing likelihoods, etc.) involves judgments or models, and results will depend on assumptions and assessments of structural uncertainties that are hard

4133 to quantify. Thus we emphasize that a solid *qualitative* understanding of how the evidence stacks  
4134 up is at least as important as any probabilities we assign. Nonetheless, sensitivity tests shown in  
4135 section 7 suggest that our results are not very sensitive to reasonable assumptions in the statistical  
4136 approach.

## 4137 **8.2 Key findings**

4138  
4139 Each main line of evidence considered here—process knowledge, the historical warming record,  
4140 and the paleoclimate record—accords poorly with values outside the traditional “Charney” range of  
4141 1.5-4.5 K for climate sensitivity  $S$ . When these lines of evidence are taken together, because of  
4142 their mutual reinforcement, we find the “outside” possibilities for  $S$  to be substantially reduced  
4143 compared to those from individual lines of evidence. Whatever the true value of  $S$  is, it must be  
4144 reconcilable with *all* pieces of evidence; if any one piece of evidence effectively rules out a  
4145 particular value of  $S$ , that value does not become likely again just because it is consistent with  
4146 some other, weaker, piece of evidence as long as there are other  $S$  values consistent with all the  
4147 evidence (see Stevens et al., 2016). If on the other hand every value of  $S$  appeared inconsistent  
4148 with at least one piece of evidence, the evidence would need reviewing to look for mistakes. But  
4149 we do not find this situation. Instead we find that the lines are broadly consistent in the sense that  
4150 there is plenty of overlap between the ranges of  $S$  each supports. This strongly affects our  
4151 judgment of  $S$ : if the true  $S$  were 1 K, it would be highly unlikely for each of several lines of  
4152 evidence to independently point toward values around 3 K. And this statement holds even when  
4153 each of the individual lines of evidence is thought to be prone to errors.

4154  
4155 We asked the following question (following Stevens et al., 2016): what would it take, in terms of  
4156 errors or unaccounted-for factors, to reconcile an outside value of  $S$  with the totality of the  
4157 evidence? A very low sensitivity ( $S \sim 1.5$  K or less) would require *all* of the following:

- 4158
- 4159 ● Negative low-cloud feedback. This is not indicated by evidence from satellite or process-  
4160 model studies and would require emergent constraints on GCMs to be wrong. Or, a strong  
4161 and unanticipated negative feedback from another cloud type such as cirrus, which is  
4162 possible due to poor understanding of these clouds but is neither credibly suggested by any  
4163 model, nor by physical principles, nor by observations (section 3).
- 4164 ● Cooling of climate by anthropogenic aerosols over the instrumental period at the extreme  
4165 weak end of the plausible range (near zero or slight warming) based both on direct  
4166 estimates and attribution results using warming patterns. Or, that forced ocean surface  
4167 warming will be much more heterogeneous than expected and cooling by anthropogenic  
4168 aerosols is from weak to middle of the assessed range (section 4).
- 4169 ● Warming during the mid-Pliocene Warm Period well below the low end of the range inferred  
4170 from observations, and cooling during the Last Glacial Maximum also below the range  
4171 inferred from observations. Or, that  $S$  is much more state-dependent than expected in  
4172 warmer climates and forcing during these periods was higher than estimated (section 5).
- 4173

4174 In other words, each of the three lines of evidence strongly discounts the possibility of  $S$  around  
4175 1.5 K or below: the required negative feedbacks do not appear achievable, the industrial-era global  
4176 warming of nearly 1 K could not be fully accounted for, and large global temperature changes  
4177 through Earth history would also be inexplicable.

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4179 A very high sensitivity ( $S > 4.5$  K) would require *all* of the following to be true:

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- Total cloud feedback stronger than suggested by process-model and satellite studies. (Section 3).
- Cooling by anthropogenic aerosols near the upper end of the plausible range. Or, that future feedbacks will be much more positive than they appear from this historical record because the mitigating effect of recent SST patterns on planetary albedo has been at the high end of expectations (Section 4).
- Much weaker-than-expected negative forcing from dust and ice sheets during the Last Glacial Maximum (section 5). Or, a strong asymmetry in feedback state-dependence (significantly less positive feedback in cold climates than in the present, but relatively little difference in warmer paleoclimates).

Thus, each of the three lines of evidence also argues against very high  $S$ , although not as strongly as they do against low  $S$ . This is mainly because of uncertainty in how strongly “pattern effects” may have postponed the warming from historical forcing, which makes it difficult to rule out the possibility of warming accelerating in the future based on what has happened so far. Indeed, we find that the paleoclimate record (in particular, the Last Glacial Maximum) now provides the strongest evidence against very high  $S$ , while all lines provide more similar constraints against low  $S$  (paleo slightly less than the others).

An important question governing the probability of low or high  $S$  is whether the lines of evidence are independent, such that multiple chance coincidences would be necessary for each of them to be wrong in the same direction (section 6). For the most part, the various elements in low- and high- $S$  scenarios do appear superficially independent. For example, while possible model errors are identified that (if they occurred) could affect historical or paleo evidence, they mostly appear unrelated to each other or to global cloud feedback or model-predicted  $S$ . Some key unknowns act in a compensating fashion (i.e., where an unexpected factor would oppositely affect two lines of evidence, effectively cancelling out most of its contributed uncertainty). Even in the one identified possibility (see below) where an unknown could affect more than one line of evidence in the same direction, modelling indicates a relatively modest impact on the PDF.

IPCC AR5 concluded that climate sensitivity is likely ( $\geq 66\%$  probability) in the range 1.5-4.5 K. The probability of  $S$  being in this range is 93% in our Baseline calculation, and is no less than 82% in all other “plausible” calculations considered as indicators of reasonable structural uncertainty (see section 7.3). Although consistent with IPCC’s “likely” statement, this indicates considerably more confidence than the minimum implied by the statement. We also find asymmetric probabilities outside this range, with negligible probability below 1.5 K but up to an 18% chance of being above 4.5 K (7% in the Baseline calculation). This is consistent with all three lines of evidence arguing against low sensitivity fairly confidently, which strengthens in combination. Given this consensus, we do not see how any reasonable interpretation of the evidence could assign a significant chance to  $S < 1.5$  K. Moreover our plausible sensitivity experiments indicate a less-than-5% chance that  $S$  is below 2 K: our Baseline 5-95% range is 2.3-4.7 K and remains within 2.0 and 5.7 K under reasonable structural changes.

Since the extreme tails of the PDF of  $S$  are more uncertain and possibly sensitive to “unknown unknowns” and mathematical choices, it may be safer to focus on 66% ranges (the minimum for what the IPCC terms “likely”). This range in our Baseline case is 2.6-3.9 K, a span less than half that of AR5’s likely range, and is bounded by 2.3 and 4.5 K in all plausible alternative calculations considered. Although we are more confident in the central part of the distribution, the upper tail is

4229 important for quantifying the overall risk associated with climate change and so does need to be  
4230 considered (e.g., Weitzman, 1989; Sutton, 2019). We also note that allowing for “surprises” in  
4231 individual lines of evidence via “fat-tailed” likelihoods had little effect on results, as long as such  
4232 surprises affect the evidence lines independently.

4233  
4234 Our  $S$  is not the true equilibrium sensitivity ECS, which is expected to be somewhat higher than  $S$   
4235 due to slowly emerging positive feedback. Values are similar, however, because we define  $S$  for a  
4236 quadrupling of  $\text{CO}_2$  while ECS is defined for a doubling, which cancels out most of the expected  
4237 effect of these feedbacks (section 2.1). We find that the 66% ECS range, at 2.6-4.1 K (Baseline)  
4238 bounded by 2.4 and 4.6 K, is not very different from that of  $S$ , though slightly higher. Thus, our  
4239 constraint on the upper bound of the ‘likely’ range for ECS is close to that of the IPCC AR5 and  
4240 previous assessments, which formally adopt an equilibrium definition. The constraint on the lower  
4241 bound of the “likely” range is substantially stronger than that of AR5 regardless of the measure  
4242 used. The uncertainties in ECS and  $S$  assessed here are similar because each is somewhat better  
4243 constrained than the other by some subset of the evidence.

4244  
4245 Among the plausible alternate calculations (see section 7.3), the one producing the weakest high-  
4246 end constraint on  $S$  uses a uniform- $S$ -inducing prior, which shifts the ranges upward to 2.8-4.5 K  
4247 (66%) and 2.4-5.7 K (90%). Our Baseline calculation assumes feedbacks are independent (or that  
4248 dependence is unknown), which predicts a non-uniform prior PDF for  $S$ ; to predict a uniform one  
4249 requires instead assuming a known, prior dependence structure among the feedbacks (see section  
4250 7.2). Although lack of consensus on priors remains a leading-order source of spread in possible  
4251 results, we still find that sensitivity to this is sufficiently modest that strong constraints are possible,  
4252 especially at the low end of the  $S$  range.

4253  
4254 The main reason for the stronger constraints seen here in contrast to past assessments is that new  
4255 analysis and understanding has led us to combine lines of evidence in a way the community was  
4256 not ready to do previously. We also find that the three main lines of evidence are more consistent  
4257 than would be expected were the true uncertainty to be as large as in previous assessments.  
4258 While some individual past studies have assigned even narrower ranges, as discussed above,  
4259 past studies have often been overconfident in assigning uncertainty so not too much weight should  
4260 be given to any single study. We note that although we did not use GCM “emergent constraint”  
4261 studies using present-day climate system variables in our base results, our results are nonetheless  
4262 similar to what those studies suggest in the aggregate (see section 3.6 for discussion of these  
4263 studies and why they were excluded from our Baseline calculation).

4264  
4265 New models run for CMIP6 are showing a broader range of  $S$  than previous iterations of CMIP  
4266 (Zelinka et al., 2020). Our findings are not sensitive to GCM  $S$  distributions since we do not directly  
4267 rely on them (see section 6.1 ). The highest and lowest CMIP6  $S$  values are much less  
4268 consistent with evidence analyzed here than those near the middle of the range. Some of the  
4269 effects quantified in this paper with the help of GCMs were looked at only with pre-CMIP6 models,  
4270 and interpretations of evidence might therefore shift in the future upon further analysis of newer  
4271 models, but we would not expect such shifts to be noteworthy unless they involved significant  
4272 improvements in model skill against relevant observations (see below).

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## 4275 **8.3 Looking forward**

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4277 Our approach not only yields new estimates of uncertainty, but points to particular directions in  
4278 which research could most productively improve constraints in the future. Here we review these;  
4279 for more details see sections 3.7, 4.3, 5.5 and 6.2.

4280

4281 One uncertainty particularly stands out in our analysis. Recent inhomogeneities of surface warming  
4282 in the Pacific (with less or no warming in the cooler regions compared to the warmer regions) are  
4283 not fully captured by any CMIP5 coupled climate models with historical forcings, and we are  
4284 unsure whether this is due predominantly to model errors in internal variability, ocean heat uptake,  
4285 or the equilibrium forced SST warming pattern. Internal variability is strongly suspected and ocean  
4286 heat uptake errors are also likely; but if unexpected model errors in the equilibrium response  
4287 pattern are involved, this would affect both process and historical evidence, compromising the  
4288 assumed independence. A preliminary calculation (section 6.3) suggests that this issue is unlikely  
4289 to substantially change results, but the matter needs further exploration. Therefore a high priority  
4290 for further constraining climate sensitivity, especially at the high end, is to more convincingly  
4291 explain this pattern of surface warming (related to the so-called “warming hiatus”) and quantify its  
4292 impact on the planetary energy balance. It might be similarly helpful to better understand the  
4293 “Grand Hiatus” of the 1960s. Doing so would make historical warming a better constraint.

4294

4295 Process information played a significant role in our analysis (section 3), but is currently limited by  
4296 our understanding of how behavior we observe in response to short-term (i.e. inter-annual)  
4297 variability relates to feedbacks on forced climate change. Further modeling work is needed to  
4298 improve this. There has been rapid progress in recent years in the understanding of cloud  
4299 feedback mechanisms, and continued progress could substantially improve constraints—but with  
4300 much recent progress on tropical low clouds, more emphasis is needed on other cloud types.  
4301 Satellite observations that provide information on the vertical distribution of clouds and its changes  
4302 have recently proven valuable in testing model feedback predictions, and their continuation would  
4303 increase the chances of further constraints.

4304

4305 The historical record currently provides a useful constraint only against very low  $S$  but there is  
4306 potential for improvement. Better constraints on aerosol forcing have proven elusive, but with  
4307 further effort using more comprehensive models, the time- and geographic evolution of climate  
4308 signals may finally allow the cooling by aerosols and warming by greenhouse gases to be teased  
4309 apart, with the decrease in emissions from some regions providing potential for better constraints  
4310 already. Progress on quantifying “pattern effects” (see above) is also ongoing and will benefit from  
4311 improved process understanding. To fully resolve both issues may require further improvement of  
4312 climate models to better reproduce decadal climate variations. Evidence from the historical record  
4313 will also continue to grow in its power to constrain  $S$  with the gradual lengthening of the record  
4314 (with the crucial proviso that the key variables continue to be well monitored by global observing  
4315 systems). This should particularly help with disentangling aerosol cooling from greenhouse  
4316 warming, due to divergent forcing patterns with aerosol influences globally close to flat while  
4317 greenhouse gases are continuing to sharply increase.

4318

4319 Evidence from the paleo record will benefit from the continuing growth of modeling activities and  
4320 improved observation/proxy characterization of other warm periods in the geological past, which  
4321 are not yet sufficiently understood to be considered here. Additionally, research into the  
4322 magnitudes, efficacies and uncertainties of forcings in the paleoclimate periods assessed is also



4323 needed. In particular, better characterization of ice sheets, dust, and potentially other aerosol  
4324 effects are needed. How  $S$  depends on background state remains a critical topic where better  
4325 observations and modeling are needed. We strongly suggest that more work on paleoclimate be  
4326 performed with the same models that are being used for the historical and future projections.

4327  
4328 Although any single metric of global warming has limitations,  $S$  is a bedrock parameter of the  
4329 global climate system. The scientific community has had difficulty narrowing its uncertainty range  
4330 far beyond the prescient initial estimate by Charney (1979) which was based on very limited  
4331 information. While much research since has confirmed this range, we now argue that in  
4332 combination this wealth of evidence has indeed narrowed it, and shifted the central value upward.  
4333 Moreover we see prospects for research to further narrow the range in the not too distant future,  
4334 and believe that this is an important continuing goal for climate science.

4335

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5932 **Table 1.** Assessed values for  $\Delta F_{2\times CO_2}$  and climate feedbacks  $\lambda_i$  based upon the various lines of  
5933 process evidence. The “Source” column identifies which lines of process evidence support the  
5934 assessed value. If the source column has a double check mark (✓✓), then it signifies that the line of  
5935 evidence provided a usable quantitative estimate. If the source column has a single check mark  
5936 (✓), then it signifies that the line of evidence provided qualitative support for mechanisms involved  
5937 or the sign of the feedback but does not provide a usable quantitative estimate. If the source  
5938 column is without a check mark, then it signifies that the line of evidence was not used in the  
5939 assessment of that term. The reason for not using a line of evidence for a given term varies but  
5940 typically was because a line of evidence is absent or not-applicable for that term or because it  
5941 provided inconsistent or untrustworthy results. Values are reported as Gaussians in the format  
5942 N(x,y), where x is the mean, and y is the standard deviation. Means and standard deviations have  
5943 units of  $W\ m^{-2}$  for  $\Delta F_{2\times CO_2}$  and  $W\ m^{-2}\ K^{-1}$  for feedbacks.  $\Delta F_{2\times CO_2}$  is specified as a prior,  $\lambda$  and  $\lambda_{clouds}$   
5944 as a PDF, and the remaining  $\lambda_i$  as likelihood functions.  
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Term	Value	Source			
		GCMs	Observations	Process-Resolving Models	Theory
Effective Radiative Forcing from a CO <sub>2</sub> doubling $\Delta F_{2\times CO_2}$	N(+4.00, 0.30)	✓✓	✓	✓✓	✓
Planck Feedback	N(-3.20, 0.10)	✓✓	✓✓		✓✓
Water Vapor + Lapse Rate Feedback	N(+1.15, 0.15)	✓✓	✓✓	✓	✓
Surface Albedo Feedback	N(+0.30, 0.15)	✓✓	✓✓		✓
Individual Cloud Feedbacks					
High-Cloud Altitude	N(+0.20, 0.10)	✓✓	✓	✓	✓
Tropical Marine Low-Cloud	N(+0.25, 0.16)		✓✓	✓✓	✓
Tropical Anvil Cloud Area	N(-0.20, 0.20)		✓✓		✓
Land Cloud Amount	N(+0.08, 0.08)	✓✓	✓		✓
Middle Latitude Marine Low Cloud Amount	N(+0.12, 0.12)	✓✓	✓✓		✓
High Latitude Low-Cloud Optical Depth	N(+0.00, 0.10)		✓✓		✓
Total Cloud Feedback $\lambda_{clouds}$	N(+0.45, 0.33)				

Stratospheric Feedback	N(+0.00, 0.10)	✓✓	✓		
Feedbacks Induced by Atmospheric Composition Changes	N(+0.00, 0.15)	✓✓			
Climate Feedback Parameter $\lambda$	N(-1.30, 0.44)				

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**Table 2.** Emergent Constraints for  $S$  based upon present-day climate system variables and CMIP models. Emergent constraints are categorized by the type of present-day climate system variable (Columns 1 and 2) with the reference for each constraint in Column 3. Column 4 reports the authors' statements about  $S$  quoted directly from the cited reference. Column 5 reports a central estimate of  $S$  from each constraint calculated from the ordinary least squares linear regression of  $S$  on the present-day climate system variable evaluated at its observed value. The data used in these calculations are taken from that compiled by Caldwell et al. (2018). Column 6 reports a central estimate for  $\lambda$  calculated in the same manner as Column 5. The last row reports the averages and standard deviations of the data in Columns 5 and 6.

Category	Present-day climate system variable	Reference	Authors' statements about $S$	Central estimate of $S$ (K) from ordinary linear regression	Central estimate of $\lambda$ ( $W m^{-2} K^{-1}$ ) from ordinary linear regression
Low Cloud	Boundary layer cloud amount response to SST variations in subtropical stratocumulus regions (after removing the stability contribution)	Qu et al. (2014)	No statement	3.74	-1.03
	Seasonal response of boundary layer cloud amount to SST variations in oceanic subsidence regions between 20° and 40° latitude	Zhai et al. (2015)	Models consistent with observation "have $S$ higher than the multi-model mean with "an ensemble mean $S$ of 3.9 K and a standard deviation of 0.45 K"	4.13	-0.82
	Fraction of tropical clouds with tops below 850 hPa whose tops are also below 950 hPa	Brient et al. (2016)	Models consistent with observation "have $S$ between 2.4 and 4.6 K"	3.06	-1.20
	Sensitivity of cloud albedo in tropical oceanic low-cloud regions to present-day SST variations	Brient and Schneider (2016)	"Most likely $S$ estimate around 4.0 K; an $S$ below 2.3 K becomes very unlikely (90% confidence)"	3.68	-0.92



General Cloud	Difference between tropical and southern-hemisphere midlatitude total cloud fraction	Volodin (2008)	An estimate of S is “3.6 ± 0.3” (1-sigma)	3.63	-0.97
	Extent to which cloud albedo is small in warm SST regions and large in cold SST regions	Siler et al. (2017)	A likely value of S is “3.68 ± 1.30 K (90% confidence)”	3.55	-0.97
Humidity	Southern hemisphere zonal-average mid-tropospheric relative humidity in dry-zone between 8.5°–20°S	Fasullo and Trenberth (2012)	“Many models, particularly those with low S, ... are identifiably biased”	4.12	-0.96
	Tropical zonal-average lower-tropospheric relative humidity in moist convective region	Fasullo and Trenberth (2012)	“Only a few models, generally of lower sensitivity, are identifiably biased”	3.42	-1.06
	Tropospheric zonal-average relative humidity vertically- and latitudinally-resolved between 40°N and 40°S	Su et al. (2014)	“Models closer to the satellite observations tend to have S higher than the multi-model mean”	3.85	-0.90
	Strength of resolved-scale humidity mixing between the boundary layer and the lower troposphere in tropical East Pacific and Atlantic	Sherwood et al. (2014)	No specific statement	4.13	-0.76
	Strength of small-scale humidity mixing between the boundary layer and the lower troposphere in tropical convective regions	Sherwood et al. (2014)	No specific statement	3.26	-1.14
	Sum of Sherwood resolved-scale and small-scale humidity mixing	Sherwood et al. (2014)	“Observations at face value implies a most likely S of about 4 K, with a lower limit of about 3 K.”	4.07	-0.83
Precipitation	Strength of model's precipitation bias in the “double-ITCZ” (Inter-Tropical Convergence Zone) region	Tian (2015)	“S might be in the higher end of its range (~4.0 K)”	4.02	-0.87
Radiation	Net top-of-atmosphere radiation averaged over the southern hemisphere	Trenberth and Fasullo (2010)	“Only the more sensitive [higher S] models are in the range of observations”	3.53	-1.05

Temperature	Amplitude of seasonal cycle of surface temperature	Covey et al. (2000)	No specific statement	3.23	-1.16
	Strength of global-average surface temperature inter-annual variations and their temporal autocorrelation	Cox et al. (2018)	The emergent constraint "yields a central [S] estimate of 2.8 K with 66% confidence limits ... of 2.2–3.4 K."	2.91	-1.22
Circulation	Latitude of the southern edge of the Hadley cell in austral summer	Lipat et al. (2017)	Models "closer to the observations ... tend to have smaller S values"	2.80	-1.23
Average				3.60 ± 0.42	-1.01 ± 0.14

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**Table 3** : Temperature trends used to assess energy budget constraints on  $S_{hist}$ . Uncertainties are 5% and 95% ranges and exclude the contribution from internal variability (section 4.1.1). The bold row marks the baseline values chosen for the main estimate of  $S_{hist}$ , although the full range of estimates are used in assessing uncertainties.

Dataset	Time Period	Observed Blended Trend (SAT/SST) (K)	Observed Blended Trend uncertainty (K)	SAT-Blended trend from models (K)	SAT-Blended Trend uncertainty (K)	Estimated SAT Trend (K)	SAT Trend uncertainty (K)
<i>Cowtan and Way</i>	2006_2018 minus 1850–1900	0.96	±0.07	0.09	±0.04	1.02	±0.08
<b><i>Cowtan and Way</i></b>	<b>2006_2018 minus 1861–1880</b>	<b>0.94</b>	<b>±0.07</b>	<b>0.08</b>	<b>±0.04</b>	<b>1.03</b>	<b>±0.08</b>

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**Table 4** : Historic ERF medians for the full 1750–2018 period and the two time periods analyzed in this report. Half gaussians are used to create the individual PDFs for sampling unless except for the aerosol ERF in the BASELINE case which employs the unconstrained PDF from Figure 8 of Bellouin et al. (2020). The row appearing in bold-face contains the values used in the Baseline calculation.

Periods	Carbon dioxide	Other well mixed greenhouse gases	Tropospheric ozone	Stratospheric ozone	Aerosol	Land-use albedo	Stratospheric water vapor	Black Carbon on snow	Contrails	Solar	Volcanic
<i>BASELINE ERFs with Bellouin et al. (2020) unconstrained aerosol PDF</i>											
1750 to 2018	2.147	1.110	0.425	-0.050	-1.395	-0.163	0.079	0.040	0.050	0.000	-0.171
<b>1861-1880 to 2006-2018</b>	<b>1.731</b>	<b>0.969</b>	<b>0.348</b>	<b>-0.050</b>	<b>-1.179</b>	<b>-0.106</b>	<b>0.064</b>	<b>0.020</b>	<b>0.048</b>	<b>0.017</b>	<b>-0.113</b>
1850-1900 to 2006-2018	1.705	0.961	0.344	-0.050	-1.092	-0.105	0.064	0.018	0.048	0.011	0.180
<i>Modified aerosol ERF to extended Boucher et al. (2013) estimate, other columns as above</i>											
1750 to 2018					-0.842						
1861-1880 to 2006-2018					-0.667						

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**Table 5** . Comparison of our  $S_{\text{hist}}$  estimates with previous studies that are representative of the literature range of sensitivity estimates (for a complete collection see Knutti et al., 2017). Medians and 5-95% ranges are shown. The temperature estimates include the effects of internal variability (section 4.1.1). When not given, these are inferred assuming Gaussian distributions. The row appearing in bold-face contains the values used in the Baseline calculation.

Study	Periods	$\Delta F_{2\times\text{CO}_2}$ ( $\text{Wm}^{-2}$ )	$\Delta F$ ( $\text{Wm}^{-2}$ )	$\Delta N$ ( $\text{Wm}^{-2}$ )	$\Delta T$ (K)	S (K) published	Shist (K) Eqn (19)	Shist (K) Eqn (21) with uniform Shist prior
<b>This study(Cowan and Way, SAT, Bellouin et al (2020) aerosol ERF) BASELINE</b>	<b>1861–1880 2006–2018</b>	<b>4.0 (3.51,4.49)</b>	<b>1.83 (- 0.03,2.71)</b>	<b>0.6 (0.3,0.9)</b>	<b>1.03 (0.89,1.17)</b>	-	<b>3.11 (1.86,14.41)</b>	<b>4.26 (2.04,16.13)</b>
This study(Cowan and Way, Blended)	1861–1880 2006–2018	BASELINE	BASELINE	BASELINE	0.96 (0.82,1.1)		2.90 (1.73,13.52)	4.02 (1.90,16.01)
This Study BASELINE SAT, modified start dates	1850–1900 2006–2018	BASELINE	2.09 (0.25,2.96)	BASELINE	1.02 (0.9,1.14)		2.63 (1.66,10.97)	3.52 (1.80,15.33)
This Study BASELINE SAT, AR5 aerosol ERF	1861–1880 2006–2018	BASELINE	2.27 (1.45,2.98)	BASELINE	BASELINE		2.49 (1.66, 5.05)	2.79 (1.76,7.48)
Lewis and Curry, 2018	1869–1882 to 2007–2016	3.8 (3.06,4.54)	2.5 (1.68, 3.36)	0.5 (0.25, 0.75)	0.8 (0.65, 0.95)	1.5 (1.05,2.45)		
Skeie et al., 2014	observatio ns up to 2010 (from 1850 and 1945/50 for OHC)		1.5 (0.27– 2.5) in 2010		1.4 (0.79– 2.2) TCR	1.8 (0.9, 3.2)		
Skeie et al., 2018	observatio ns extended up to 2014		2.3 (1.3, 3.4)		1.4 (0.9, 2.0) TCR	2.0 (1.2, 3.1)		
Johansson et al., 2015	observatio ns up to 2011 (from 1880, 1957 for OHC)	3.71	2.29 (ERF from IPCC AR5 Table 8. SM5)		0.37–11.1 (prior ECS range for CO2 doubling)	N/A (2.0, 3.2) 90% CI  2.50 mode		

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5988 **Table 6** . Statistics of the likelihood  $P(E_{\text{hist}}|S)$  combined with a uniform prior (from 0 to 20 K) on  
 5989 S, based on the two different estimates of future feedback changes as outlined above. The  
 5990 method based on prescribed observed SST patterns is chosen as the preferred estimate (in bold).

Scaling method	Max likelihood (K)	Median (K)	5% value (K)	95% value (K)
None	2.5	4.3	2.0	16.1
Transient simulations	2.9	6.2	2.3	17.9
<b>Observed SST pattern</b>	<b>3.8</b>	<b>8.5</b>	<b>2.8</b>	<b>18.6</b>

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5993 **Table 7** . Parameters of the distributions that are used to estimate  $S$  from the cold climate states  
 5994 (equation 5.1). Radiative forcing per  $\text{CO}_2$  doubling from section 3.2.1.

Term	Distribution
$\Delta T$ (K)	N(-5, 1)
$\Delta F_{2\times\text{CO}_2}$ ( $\text{Wm}^{-2}$ )	N(4.0, 0.3)
$\Delta F'$ ( $\text{Wm}^{-2}$ )	N(-6.15, 2)
$\alpha$	N(0.1, 0.1)
$\zeta$	N(0.06, 0.2)

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5996 **Table 8** . Parameters of the distributions that are used to estimate  $S$  from the mPWP, equation  
 5997 5.2. Radiative forcing per  $\text{CO}_2$  doubling from section 3.2.1.

Term	Distribution
$\Delta T$ (K)	N(3, 1)
$\text{CO}_2$ (ppm)	N(375, 25)
$\Delta F_{2\times\text{CO}_2}$ ( $\text{Wm}^{-2}$ )	N(4.0, 0.3)
$f_{\text{CH}_4}$	N(0.4, 0.1)
$f_{\text{ESS}}$	N(0.5, 0.25)
$\zeta$	N(0.06, 0.2)

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6000 **Table 9** . Parameters of the distributions that are used to estimate S from the PETM, equation  
6001 5.3. Radiative forcing per CO<sub>2</sub> doubling from section 3.2.1.

Term	Distribution
$\Delta T(K)$	N(5, 1)
CO <sub>2</sub> (ppm)	N(2400, 700)
$\Delta F_{2\times\text{CO}_2} (Wm^{-2})$	N(4.0, 0.3)
$f_{\text{CH}_4}$	N(0.4 ,0.2)
$\beta$	N(0, 0.5)
$\zeta$	N(0.06, 0.2)

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	5th %ile	17th %ile	50th %ile	83rd %ile	95th %ile	Mode	Mean
Baseline (UL, Uniform $\lambda$ Prior)*	2.3	2.6	3.1	3.9	4.7	3.0	3.2
US (Uniform S Prior)*	2.4	2.8	3.5	4.5	5.7	3.1	3.7
UL No Process	2.0	2.4	3.1	4.1	5.2	2.7	3.3
UL No Historical*	2.0	2.3	2.9	3.7	4.6	2.6	3.1
UL No Paleo Warm*	2.2	2.5	3.1	4.0	5.1	2.9	3.3
UL No Paleo Cold*	2.3	2.6	3.2	4.1	5.1	3.0	3.4
UL No Paleo	2.2	2.6	3.3	4.6	6.4	2.9	3.8
US No Process	2.3	2.8	3.7	5.2	6.9	3.1	4.0
UL + EC (Emergent Constraints)	2.4	2.7	3.2	4.0	4.8	3.1	3.4
Fat tails	2.2	2.5	3.1	4.0	4.9	2.8	3.3

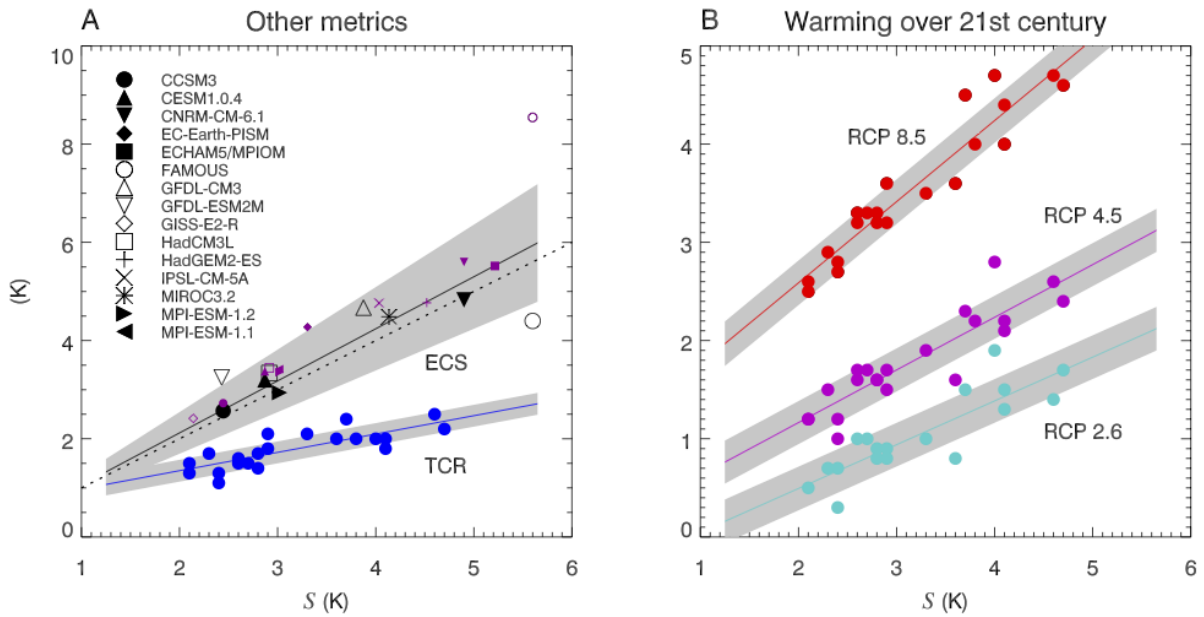
6004 **Table 10.** Mean, Mode, Median and percentile values of posterior PDFs for S. Sensitivity tests  
 6005 considered to bound plausible structural uncertainty are marked with a \*. Further statistics are  
 6006 available in the online data repository (see Acknowledgments).  
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	Baseline	Uniform-S PPD
<b>ECS</b>	3.2 [2.6,4.1]	3.5 [2.7,4.6]
<b>TCR</b>	1.8 [1.5, 2.2]	1.9 [1.6, 2.4]
<b>RCP2.6 warming</b>	1.0 [0.7, 1.4]	1.2 [0.8, 1.7]
<b>RCP4.5 warming</b>	1.8 [1.4, 2.3]	2.0 [1.5, 2.6]
<b>RCP6.0 warming</b>	2.0 [1.6, 2.6]	2.3 [1.7, 3.0]
<b>RCP8.5 warming</b>	3.5 [3.0, 4.2]	3.8 [3.2, 4.8]

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 6012 **Table 11** . Medians and 66% probability ranges (in brackets), for ECS (for one doubling of CO<sub>2</sub>),  
 6013 TCR, and warmings in Fig. 23 , for our Baseline and using a uniform prior on S. All values in K.  
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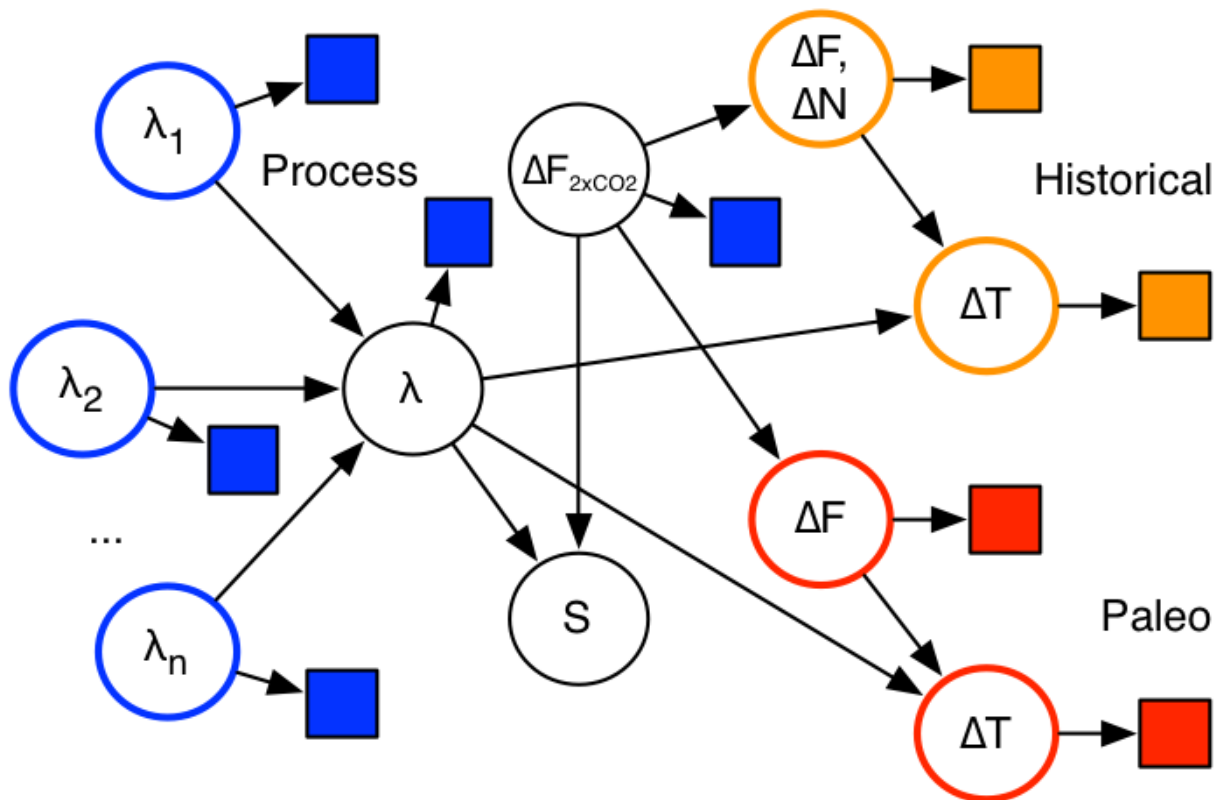


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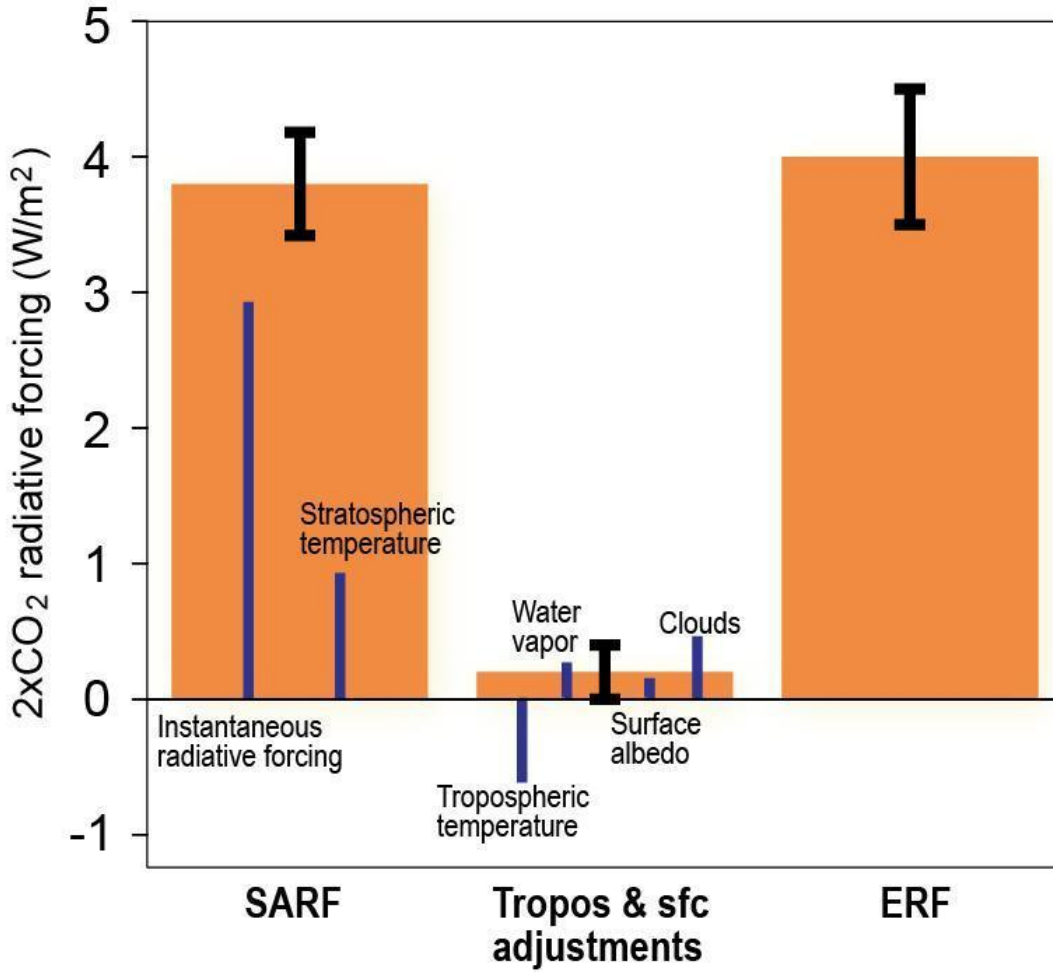
**Figure 1.** Relation of (a) other climate sensitivity metrics, and (b) predicted warming by late this century, to  $S$  as defined in section 2.1. In (a), symbols show 15 LongRunMIP model estimates of the equilibrium warming per doubling of  $\text{CO}_2$  (Rugenstein et al., 2019b), with small purple symbols showing equilibria in  $4x\text{CO}_2$  simulations and large black symbols equilibria in  $2x\text{CO}_2$  simulations. Blue filled circles show TCR from CMIP5 models. In (b), projected change in global-mean temperature in 2079–2099 relative to 1986–2005, under the RCP8.5 (red), RCP4.5 (magenta) and RCP2.6 (cyan) scenarios, from 24 CMIP5 models. CMIP5 data are from Grose et al. (2018). For each set of points, a best linear fit is shown, with one standard deviation shown in grey shading (assumed homogeneous except for ECS where it is assumed to scale linearly with  $S$ ); see section 7.4 for further details on fits.



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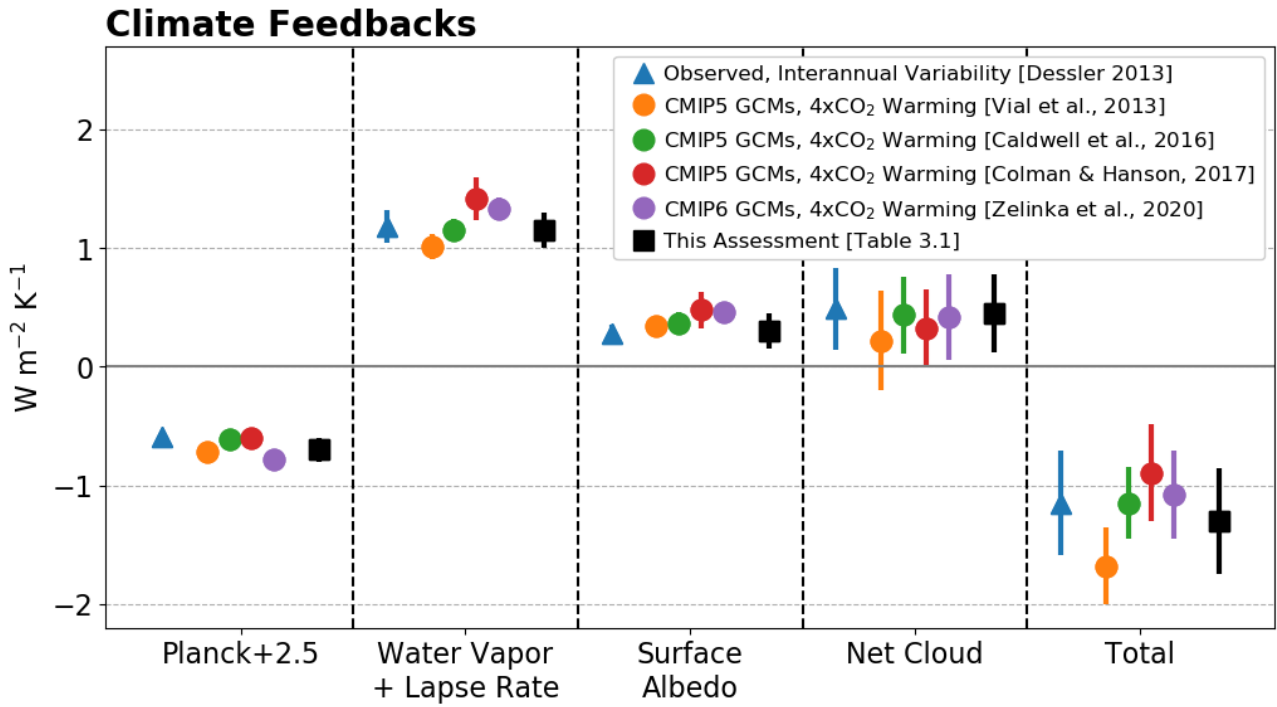
**Figure 2.** A Bayesian network diagram showing the dependence relationships between main variables in the inference model. Circles show uncertain variables, whose PDFs are estimated; squares show evidence (random effects on the evidence would appear as a second “parent” variable for each square, and are omitted for simplicity). Colors distinguish the three main lines of evidence and associated variables (blue = process, orange = historical, red = paleoclimate). For paleoclimate, only one  $\Delta F/\Delta T$  climate-change pair is shown but two independent ones are considered (see section 5).

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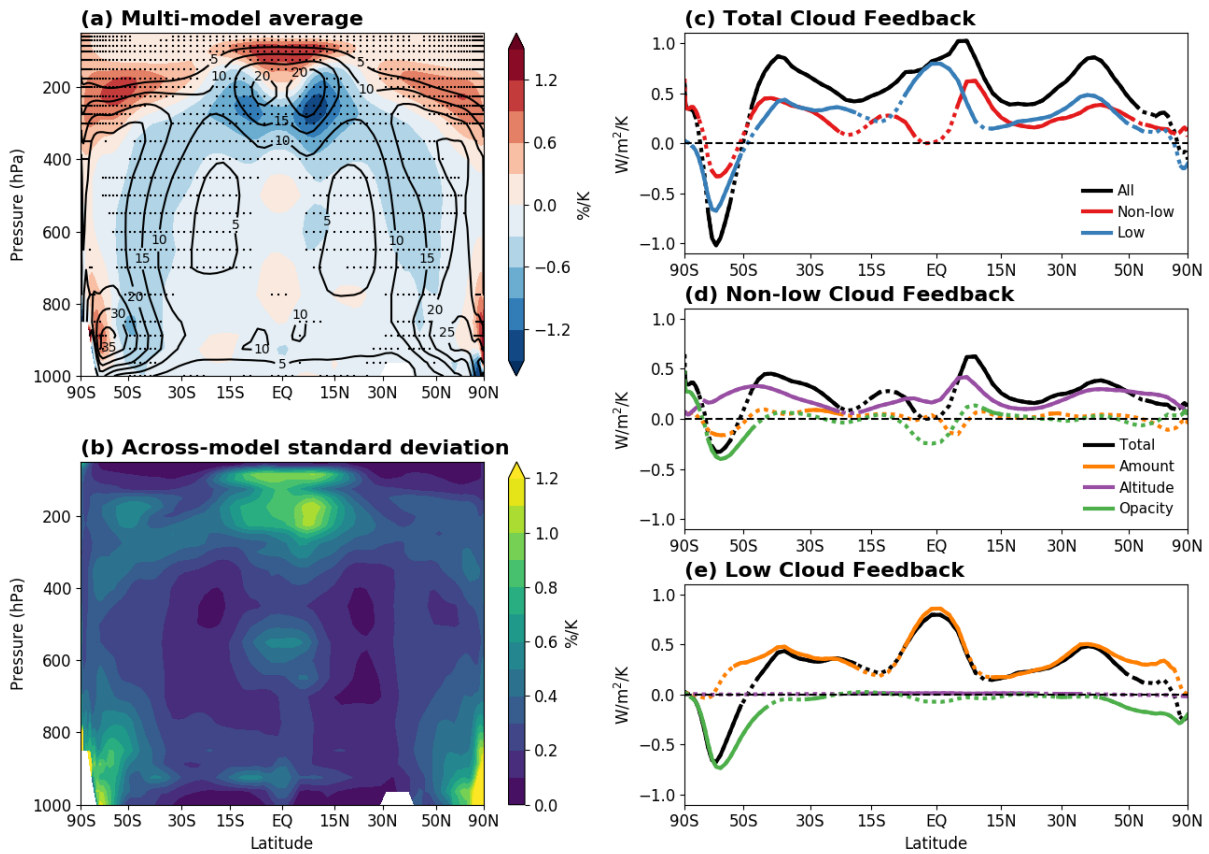
**Figure 3** . Assessed values of the 2xCO<sub>2</sub> Effective Radiative Forcing (ERF) at the TOA. Orange bars represent Stratospheric-Adjusted Radiative Forcing (SARF), tropospheric and surface albedo adjustments, and their sum (i.e., ERF). The error bar indicates the 5-95% ranges of the respective terms. Further decomposed components are presented for reference by blue bars based on Etmnan et al. (2016) and Smith et al. (2018). The contribution from land surface warming has been excluded in the surface adjustment.



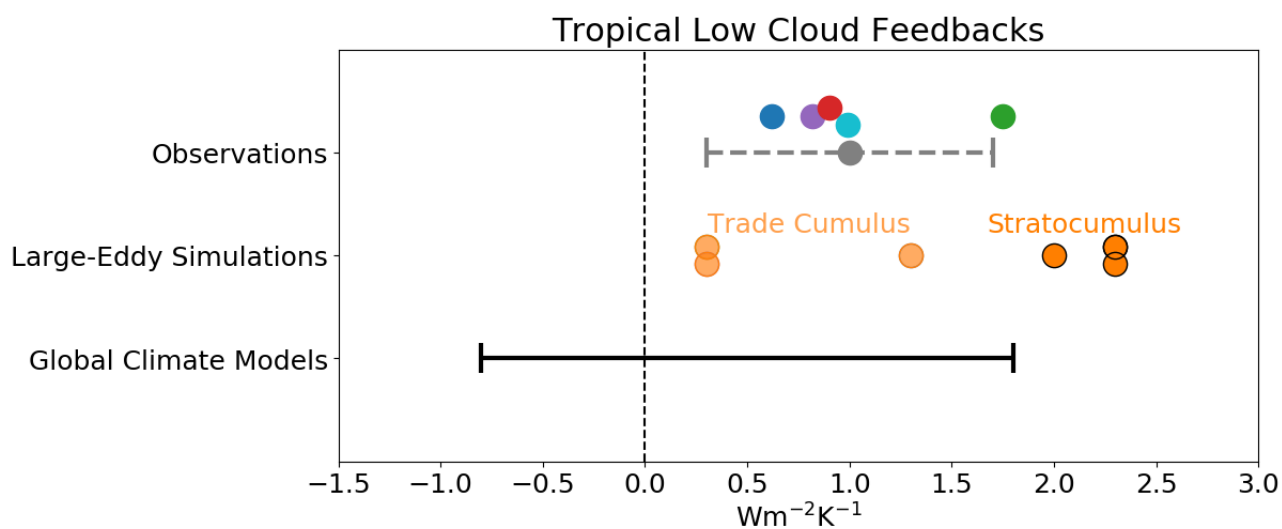
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**Figure 4** . Estimates of global mean climate feedbacks from observations of interannual variability (blue triangles), from CMIP5 and CMIP6 model simulations of global warming in response to an abrupt CO<sub>2</sub> quadrupling (colored circles—orange: Vial et al., 2013; green: Caldwell et al., 2016; red: Colman and Hanson, 2017; purple: Zelinka et al., 2020), and from this assessment (black squares). Error bars on climate model feedback estimates span the 1-standard-deviation range across models. Observational estimates are derived using a combination of ERA-Interim meteorological fields and CERES TOA radiative fluxes (Loeb et al., 2009) covering the period 03/2000 to 12/2010 (Dessler, 2013). Error bars on the observational estimates are 1-sigma uncertainties, accounting for autocorrelation. Individual feedbacks are computed by multiplying temperature-mediated changes in relevant fields by radiative kernels (Shell et al., 2008; Soden et al., 2008; Huang et al., 2017). Error bars on values from this assessment correspond to 1-sigma uncertainties. Note that Planck feedback estimates are offset by 2.5 W m<sup>-2</sup> K<sup>-1</sup> from their actual values in order that they appear within the plot range.

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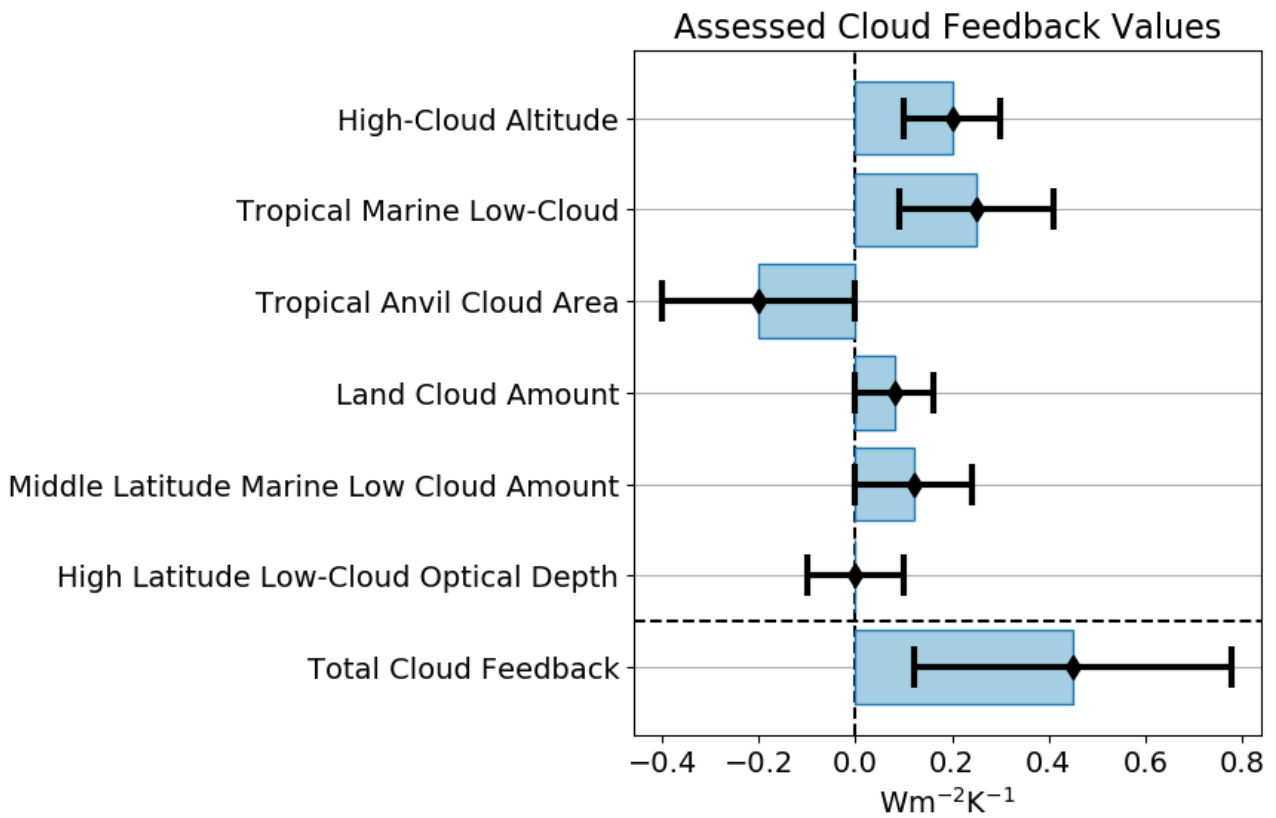


**Figure 5** . Multi-model and zonal-mean cloud diagnostics: (a) Mean cloud fraction (contours, every 5%) and warming response (shading), with stippling where at least 20 of the 25 contributing CMIP5 models agree on the sign of the response; (b) Inter-model standard deviation of cloud fraction response; (c) Total cloud feedback from all clouds and also partitioned into contributions from low (cloud top pressures > 680 hPa) and other ('non-low', cloud top pressures < 680 hPa) clouds; (d) non-low- and (e) low-cloud feedback partitioned into amount, altitude, and optical-depth responses to warming. Latitudes where at least 14 of the 18 contributing models agree on the sign of the feedback are plotted with a solid line. Feedbacks in (c-e) are calculated from abrupt4xCO2 simulations of 7 CMIP5 models and from equilibrium 2xCO2 simulations of 11 CMIP3 slab-ocean models (see Zelinka et al., 2016, for details). Note that all plots use an area-weighted latitude scale. Figure based upon Zelinka et al. (2016).



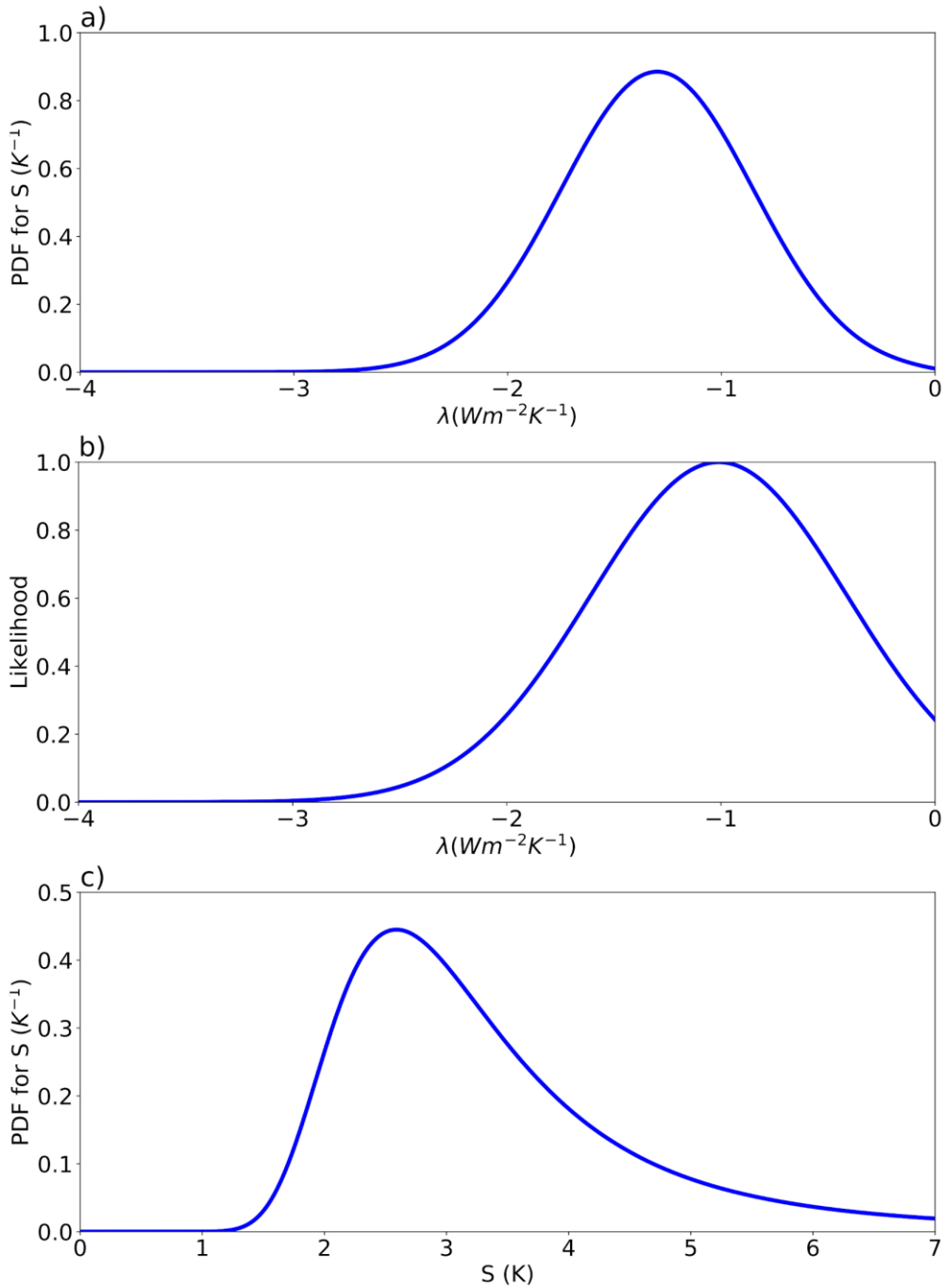
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**Figure 6** . Local tropical low-cloud feedbacks from observations, large-eddy simulations, and global climate models from Klein et al. (2017). Each dot represents the feedback from an individual research study. The upper horizontal bar indicates the central estimate and 90% confidence interval for the feedback inferred in that study from the observations. The lower bar indicates the range of feedbacks simulated by global climate models. Note that our assessment reinterprets the upper horizontal bar into a likelihood statement assuming a uniform prior and with considering additional evidence (section 3.3.2).



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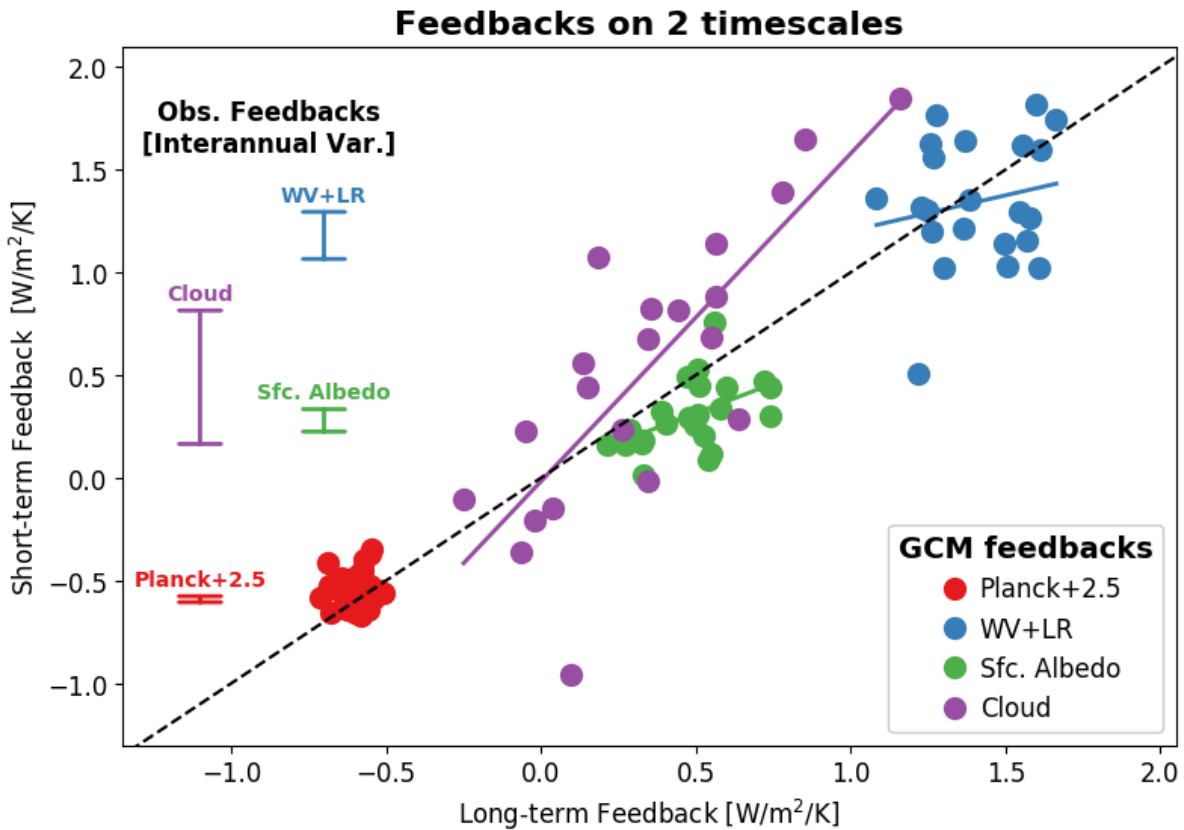
**Figure 7** . Assessed values of individual cloud feedbacks and the total cloud feedback based upon process evidence. For individual cloud feedbacks, maximum likelihood values are shown by black diamonds and the widths of blue rectangles, with two times the 1-sigma likelihood values shown by the width of the black uncertainty bars. For the total cloud feedback, the mean value of the PDF is shown by a black diamond and the width of the accompanying blue rectangle, with two times the PDF standard deviation shown by the width of the black uncertainty bar.



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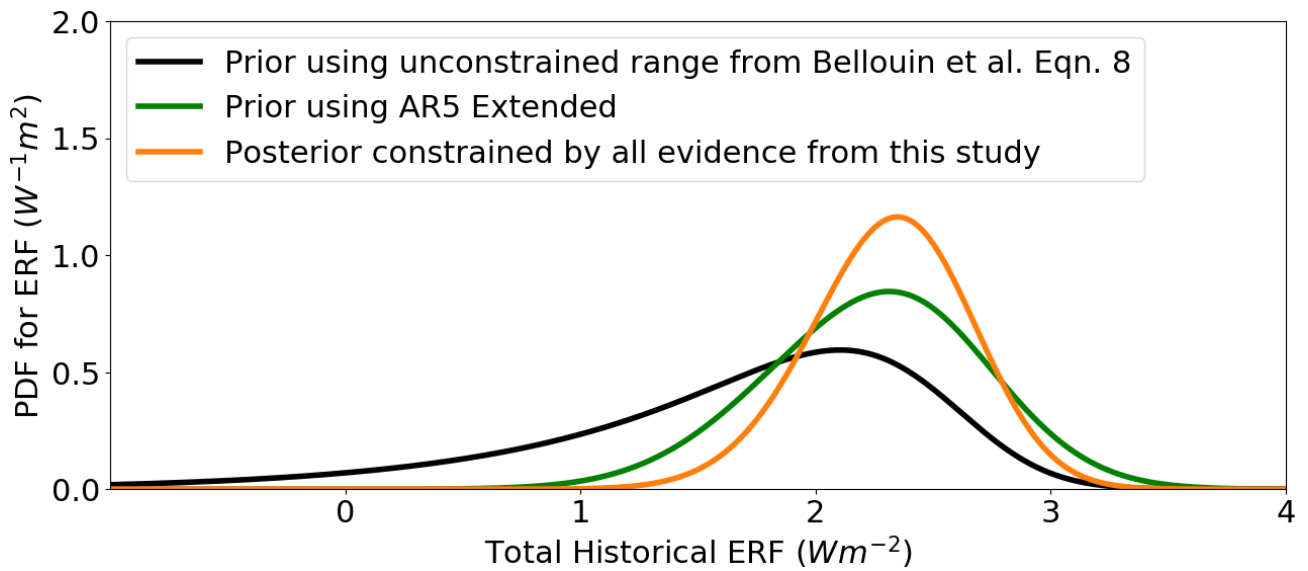
**Figure 8** . PDFs and likelihood functions based upon the assessment of individual climate feedbacks and the emergent constraint literature. (a) PDF for  $\lambda$  from combining evidence on individual feedbacks using the Baseline  $\lambda_i$  prior. (b) Emergent Constraint likelihood for  $\lambda$ . Note that this likelihood is not a PDF. See section 3.6 for an explanation of how the parameters of this likelihood function were determined and why they differ from the parameters recorded in Table 2. (c) PDF for  $S$  from combining evidence on  $\Delta F_{2xCO_2}$  and individual feedbacks using uniform  $\lambda_i$  priors.





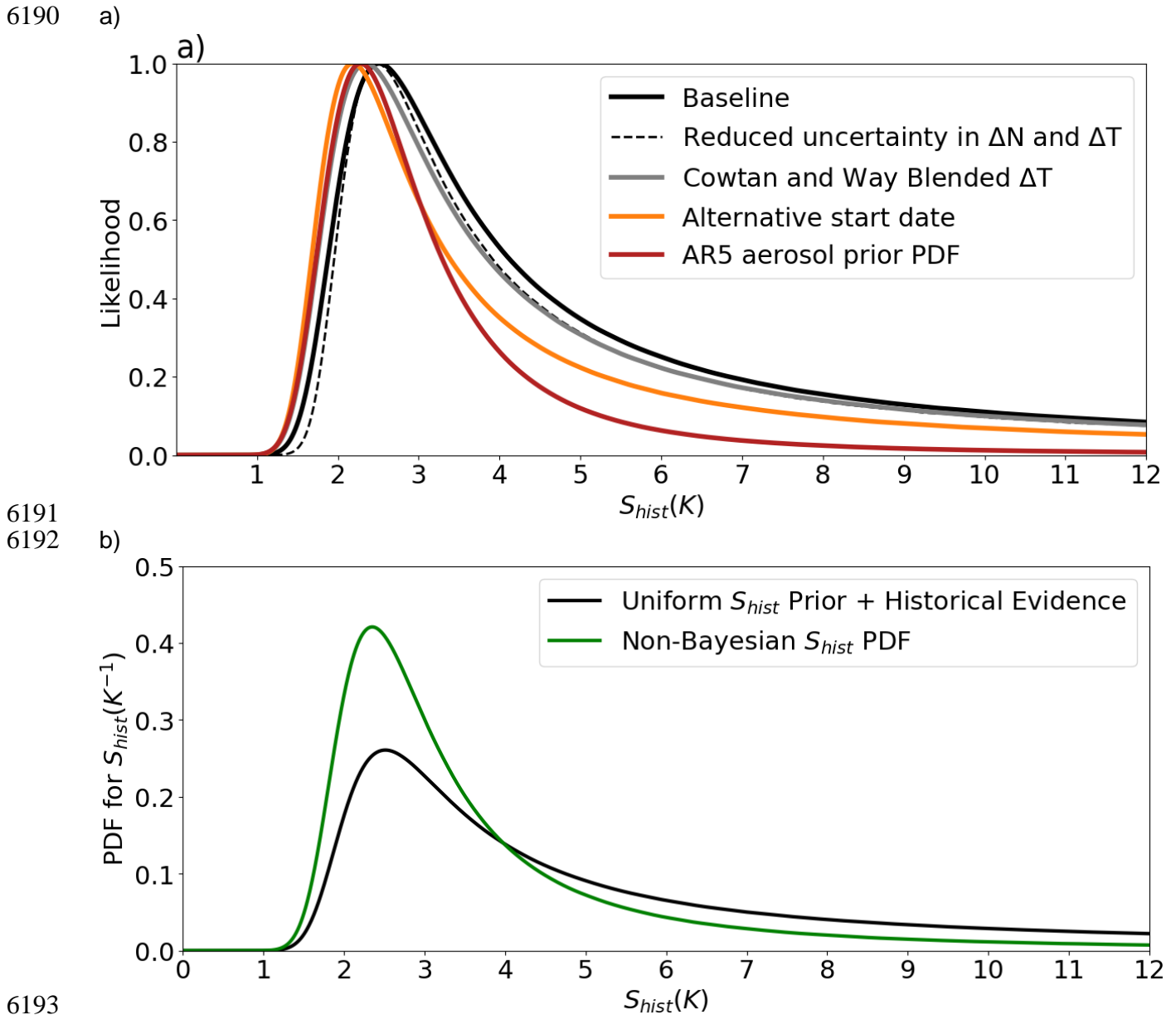
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**Figure 9** . Individual feedbacks in CMIP5 climate models (circular symbols) and inferred from observations (error bars along the y-axis). The y-axis displays relationships derived from natural variability at the inter-annual time-scale using 100 years of pre-industrial control simulations from CMIP5 climate models (Colman and Hanson, 2017) and using ~11 years of observations between March 2000 and December 2010 (Dessler, 2013). Error bars span the 1-sigma uncertainties of the observed feedback estimates. The x-axis displays the long-term feedbacks from climate model simulations of the response to an abrupt quadrupling of  $CO_2$  (Colman and Hanson, 2017) The black dashed line is the 1:1 line whereas the short solid thick lines among the climate model points display the ordinary least-squares linear regression lines between simulated inter-annual and long-term feedbacks.

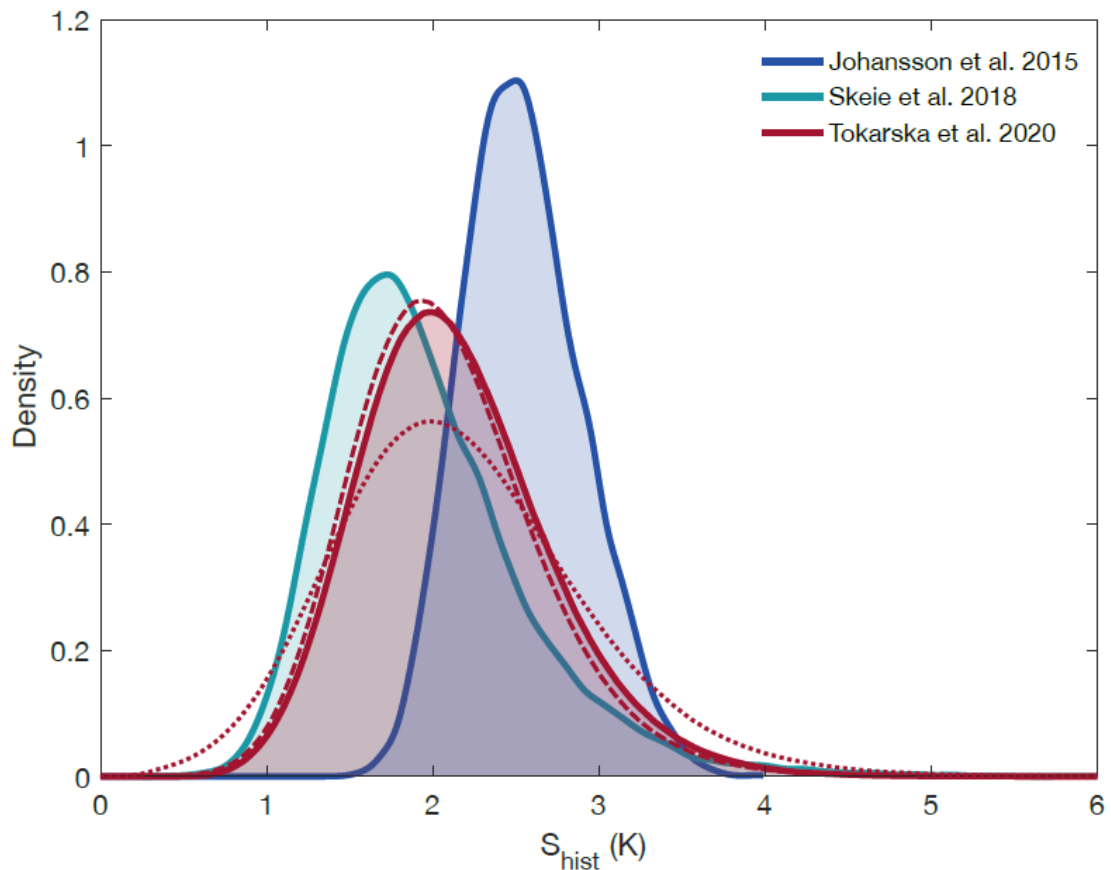


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**Figure 10** . Prior and posterior PDFs of total (anthropogenic plus natural)  $\Delta F$  ( $Wm^{-2}$ ), comparing the 2006–2018 period with the 1861–1880 period. The black curve shows the prior forcing used in the Baseline calculation, which uses the unconstrained aerosol forcing based on Eqn. (8) from Bellouin et al. (2020). The green curve shows the extended AR5 aerosol forcing. The orange curve shows the posterior PDF produced when all prior PDFs are updated by all evidence used in the full Baseline calculation (see section 7), including process, historical and paleoclimate evidence.

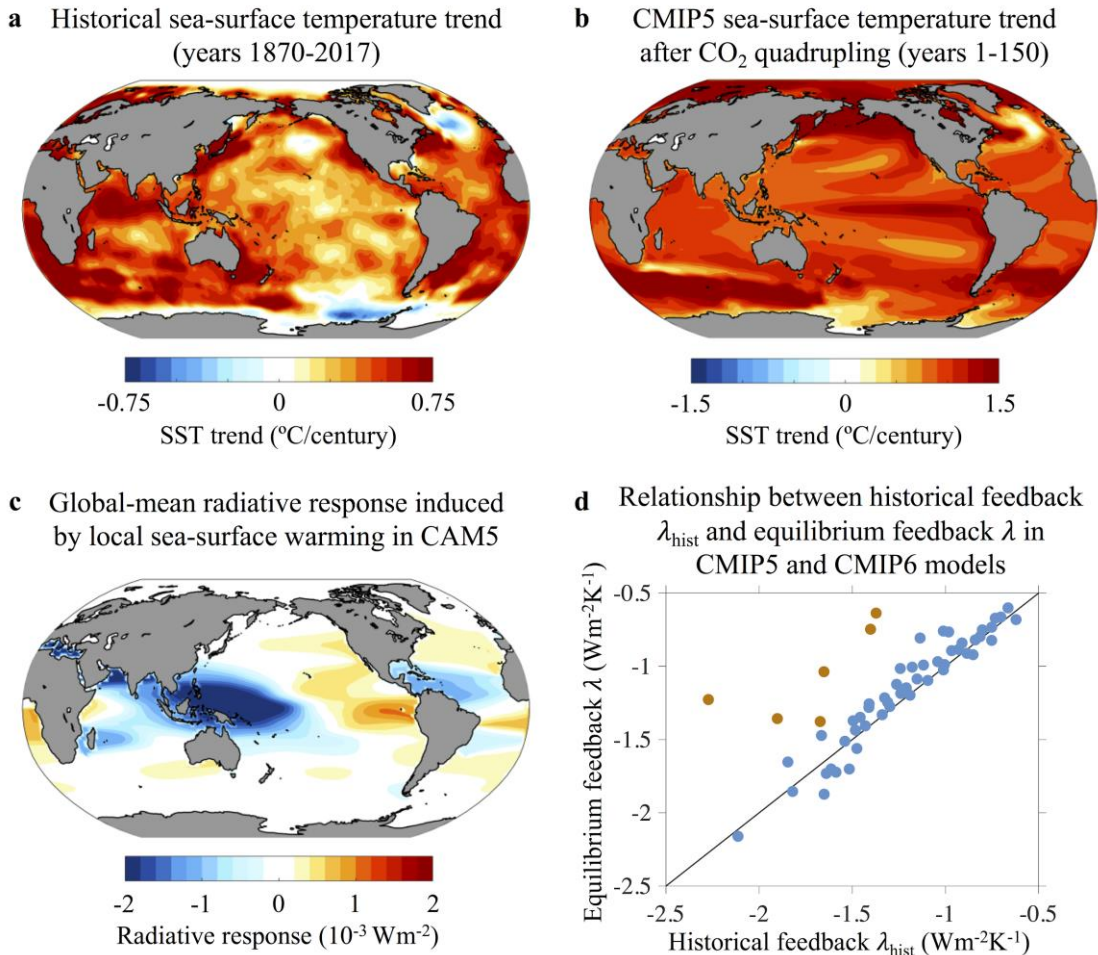


6195 **Figure 11** . (a) Likelihood function for  $S_{hist}$  derived from the planetary energy budget of the 2006  
 6196 –2018 period compared to the 1861–1880 period. Different analyses are shown based on the  
 6197 alternative estimates in Table 5. The dashed line shows the impact of reducing the uncertainty  
 6198 in  $\Delta T$  and  $\Delta N$  by 90%. The gray line shows the impact of using the original Cowtan and Way  
 6199 (2014) blended dataset that mixes surface air temperature observations with sea-surface  
 6200 temperature observations. The orange line shows the impact of using 1850–1900 for the earlier  
 6201 period, while the red line shows the impact of using the AR5 aerosol forcing. (b) PDF of  $S_{hist}$  based  
 6202 on likelihood function in (a) combined with a uniform prior on  $S_{hist}$  (black line) and PDF derived  
 6203 directly from Equation 19 (green line).  
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6209 **Figure 12** : Illustration of probability density functions from alternative, published approaches  
 6210 (as labelled). Tokarska et al. (2020) relies on an energy budget approach using the observed  
 6211 warming and ocean heat uptake attributed to greenhouse warming, and is most directly  
 6212 comparable to our main approach. The solid line relies on a flat prior in  $S$ , the dashed line is  
 6213 directly sampled (see text; similar to green line in Figure 11 ), and the dotted line is the same as  
 6214 the solid line, but based on doubled variance of climate variability when deriving the attributed  
 6215 warming estimates. Johansson et al. (2015) and Skeie et al. (2018) results are based on time-  
 6216 space analysis using simple climate model fits to observations and are also depicted for a uniform  
 6217 prior in  $S$ . Results suggest that use of time-space patterns (either in simple model fits or deriving  
 6218 attributed surface and ocean warming) reduce the upper tail of climate sensitivity, yet are affected  
 6219 by uncertainty in methods used, particularly if using simple models.

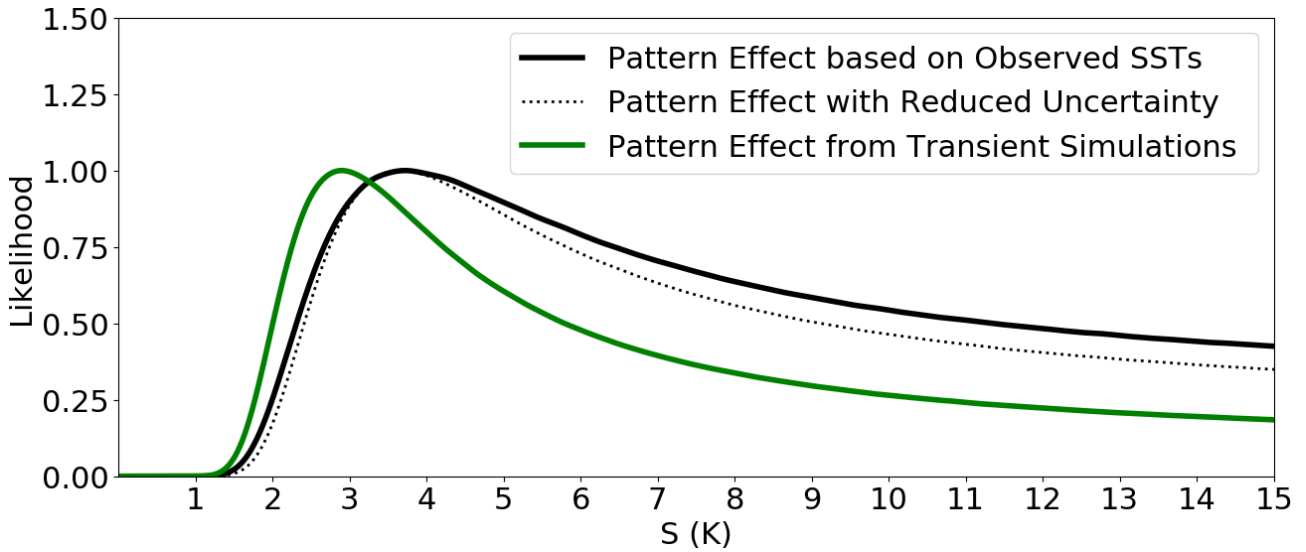
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**Figure 13** : Illustration of the pattern effect. (a) Linear trend in observed sea-surface temperatures (SSTs) over years 1870–2017 from the AMIP2 dataset (Hurrell et al., 2008). (b) Linear trend in CMIP5-mean SSTs over 150 years following abrupt CO<sub>2</sub> quadrupling. (c) Global-mean TOA radiative response induced by perturbing SSTs in one region at a time, calculated as anomalous TOA radiative fluxes in response to local SST perturbations in NCAR’s Community Atmosphere Model version 5 (CAM5) (Zhou et al., 2017; see also Dong et al., 2019 for comparison to CAM4). (d) Relationship between historical feedbacks  $\lambda_{hist}$  and the long-term  $\lambda$  in coupled CMIP5 and CMIP6 models using values from analysis in Lewis and Curry (2018) and Dong et al. (2020) (blue points), respectively, and for atmosphere-only simulations from Andrews et al. (2018) (orange points).

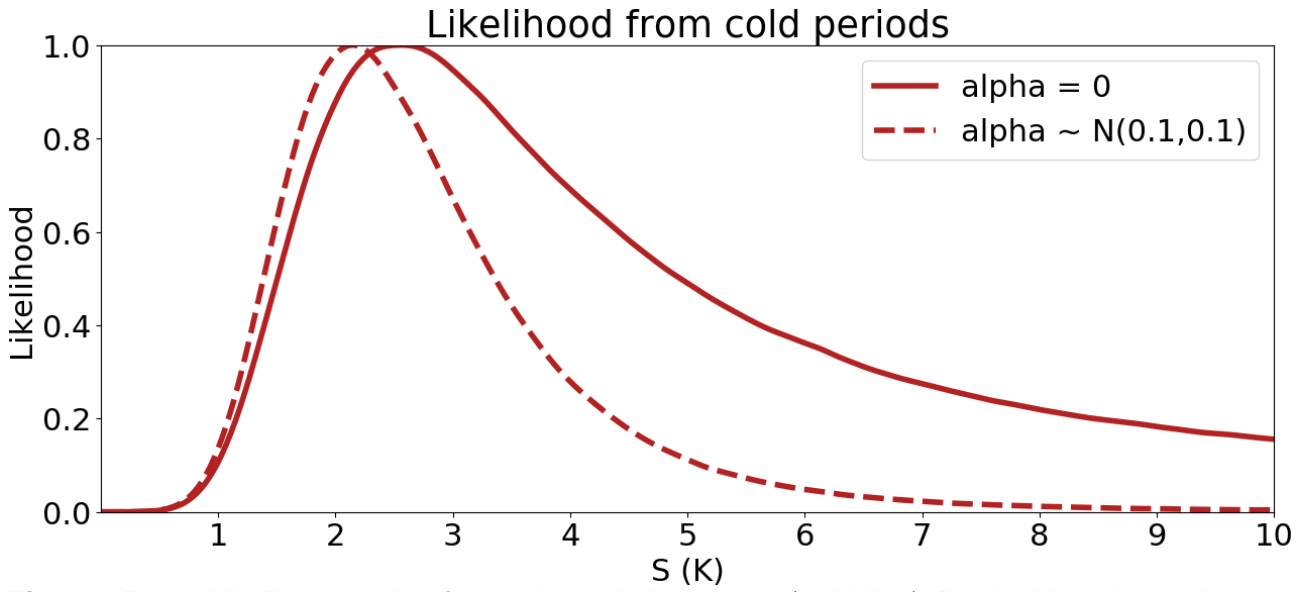
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6241 **Figure 14** . Likelihoods for  $S$  based on historical energy budget estimates accounting for pattern  
6242 effects using different methods. The black curve shows the likelihood we use for our main analysis  
6243 in section 7 which is based on feedback changes estimated using observed SST patterns  
6244 (Andrews et al., 2018) but with inflated uncertainty to account for several considerations described  
6245 in the text. The dotted black line shows the effect of halving the uncertainty in  $\Delta\lambda$ . The green line  
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6247 coupled climate models (Armour, 2017).  
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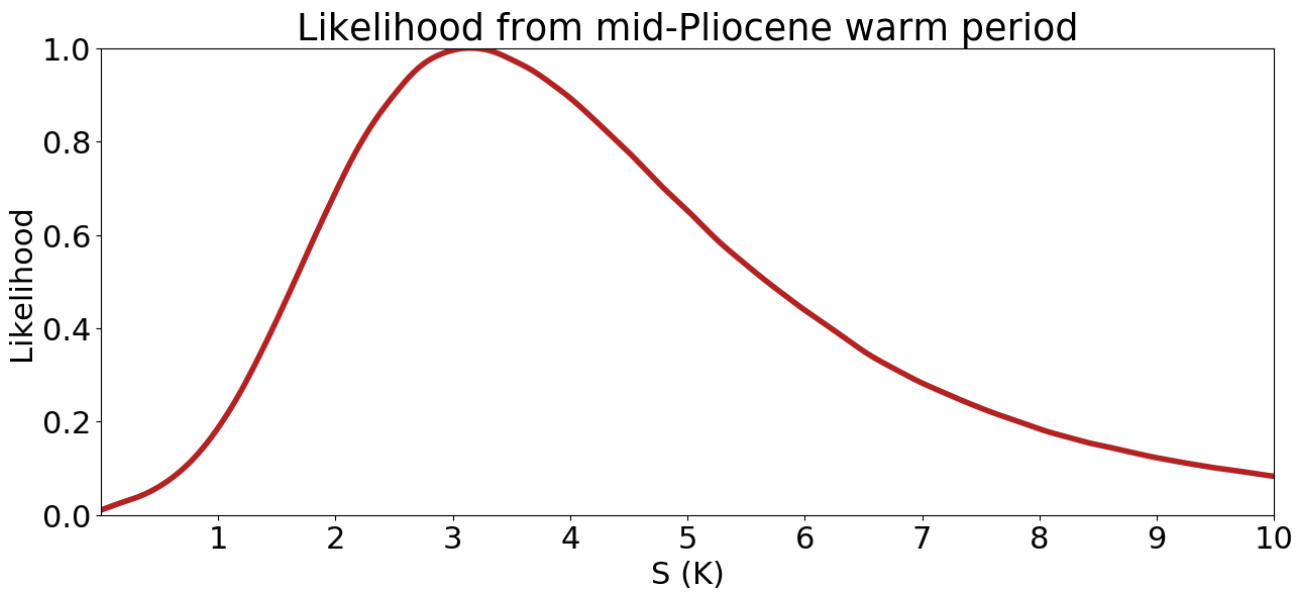
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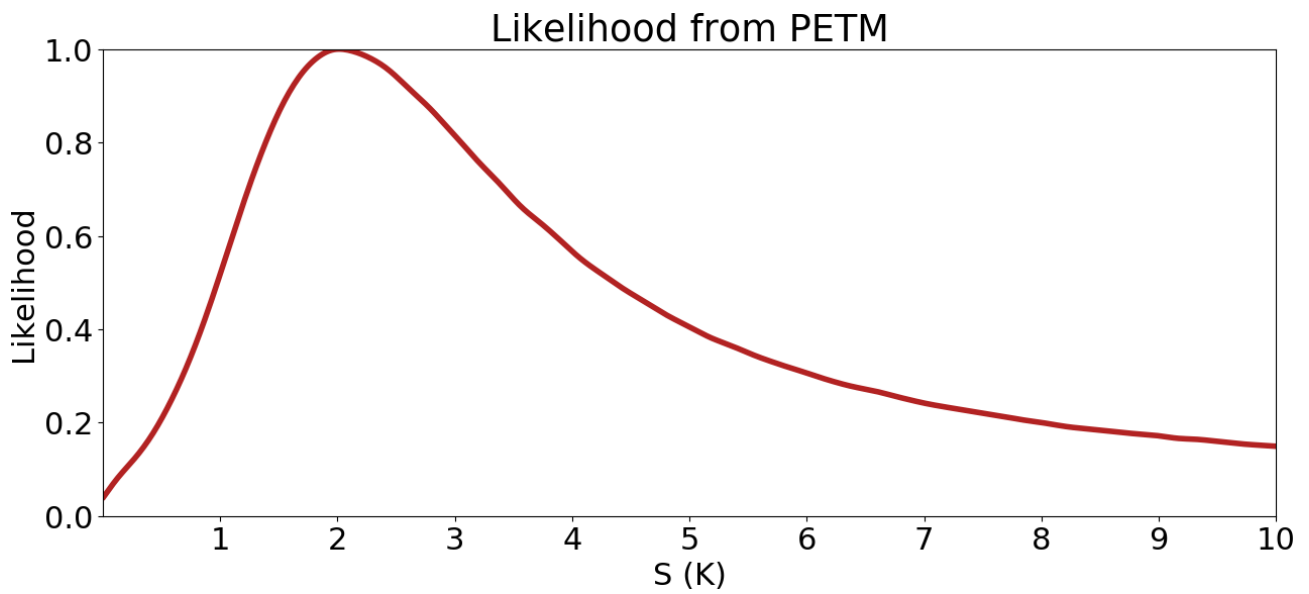
**Figure 15** . Likelihood arising from cold-period evidence (solid line). Dashed line shows the likelihood that would arise if state dependence of  $\lambda$  were omitted ( $\alpha = 0$ ).



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**Figure 16** . Likelihood arising for mPWP.



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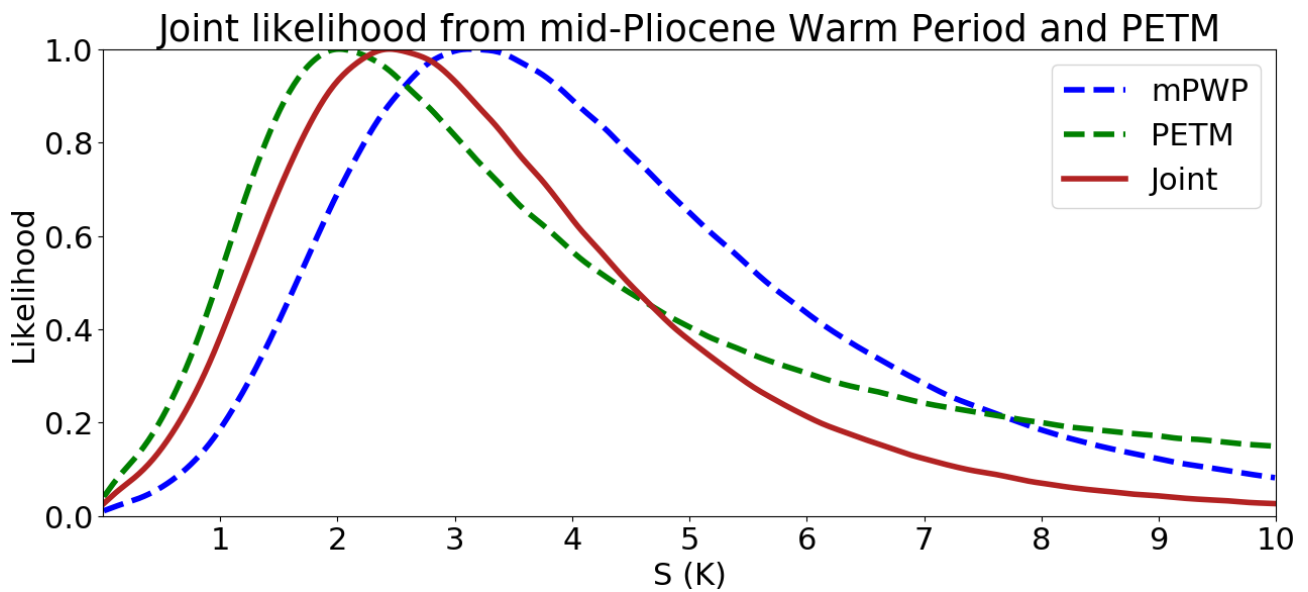
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**Figure 17** . Likelihood arising for the Paleocene-Eocene Thermal Maximum. The maximum likelihood value of around 2 K corresponds to a 5 K warming and  $\sim 3\times\text{CO}_2$  change together with its accompanying  $\text{CH}_4$  increase.

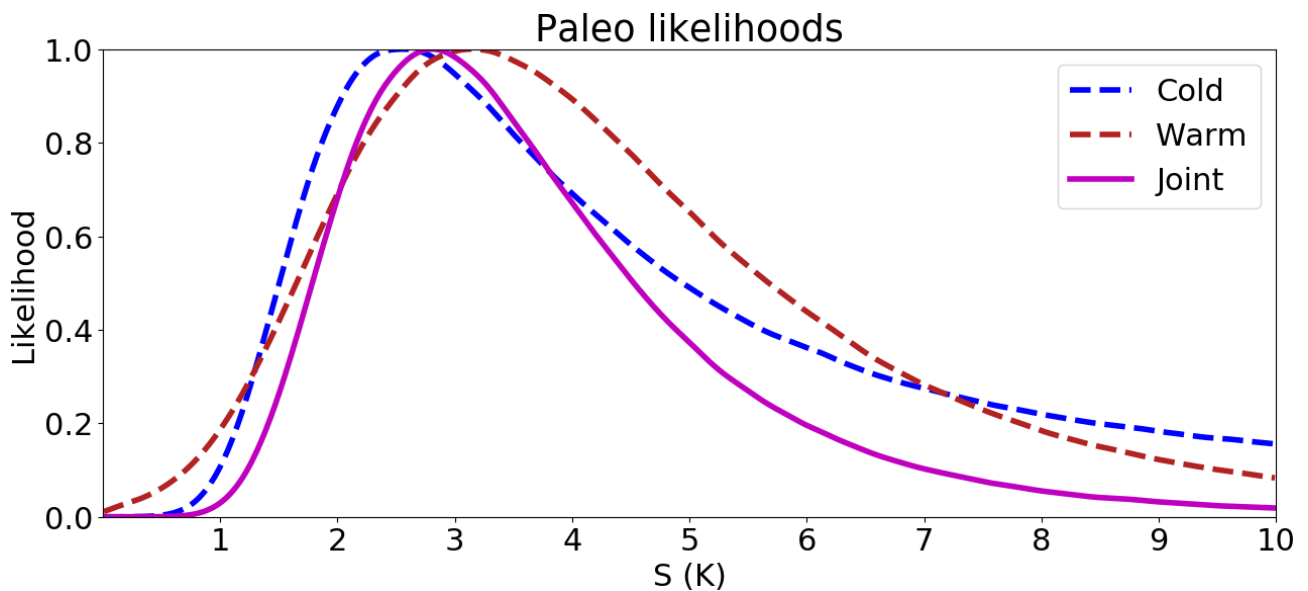




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6264 **Figure 18** . Analysis of mPWP and PETM results. Blue and green dashed lines are mPWP and  
 6265 PETM results as previously shown. Red line is joint likelihood obtained accounting for dependency  
 6266 as described in the text. As explained in section 5.3.2, the mPWP result is our proposed result.

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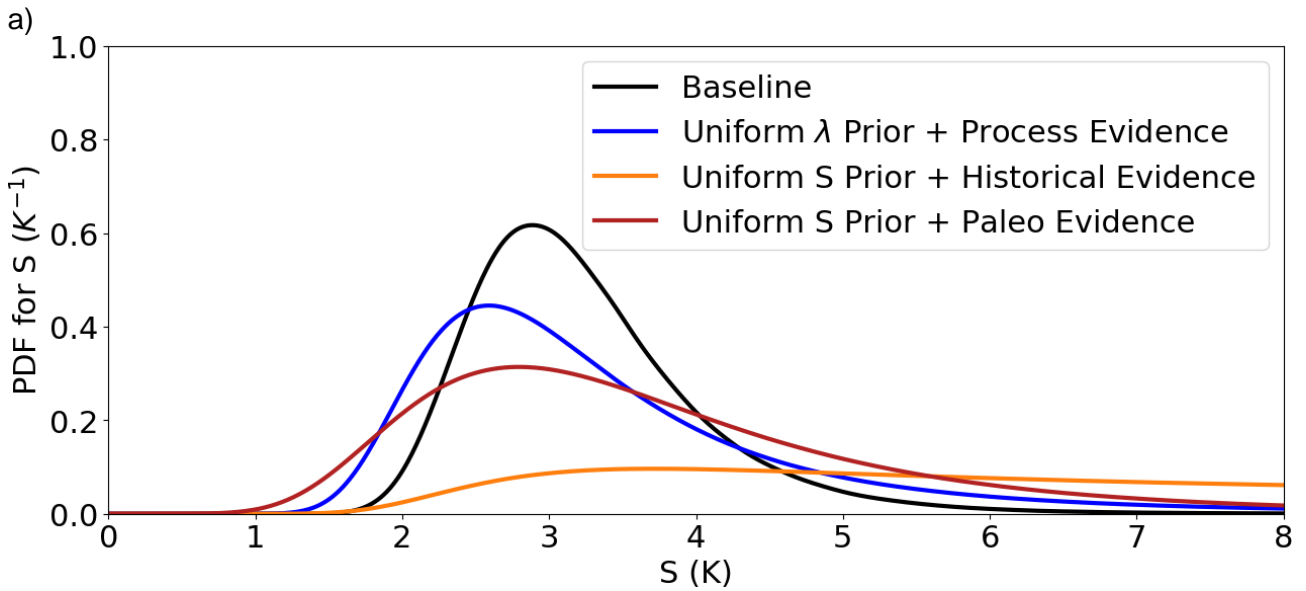
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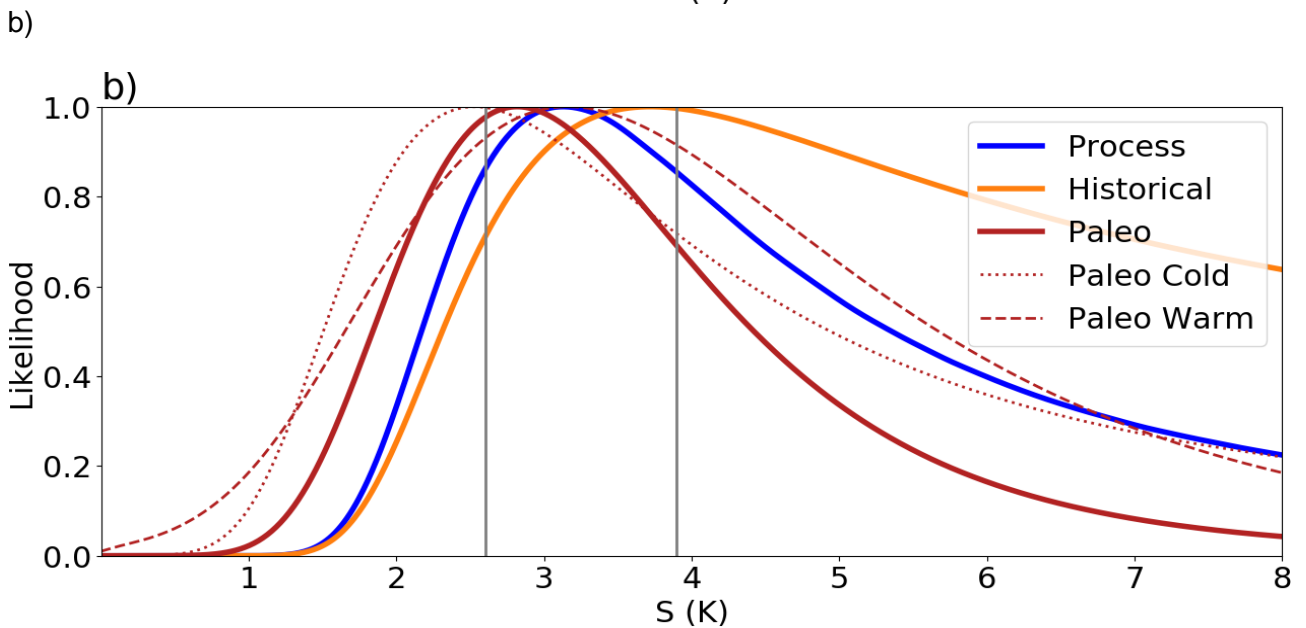
6270 **Figure 19** . Blue-dashed is the cold periods' likelihood. Red-dashed is the warm periods'  
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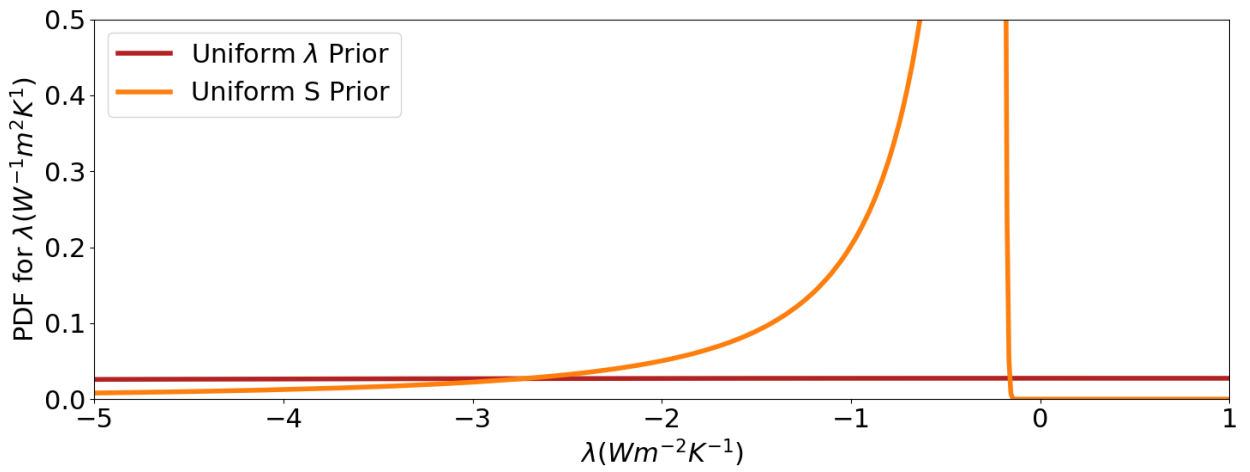
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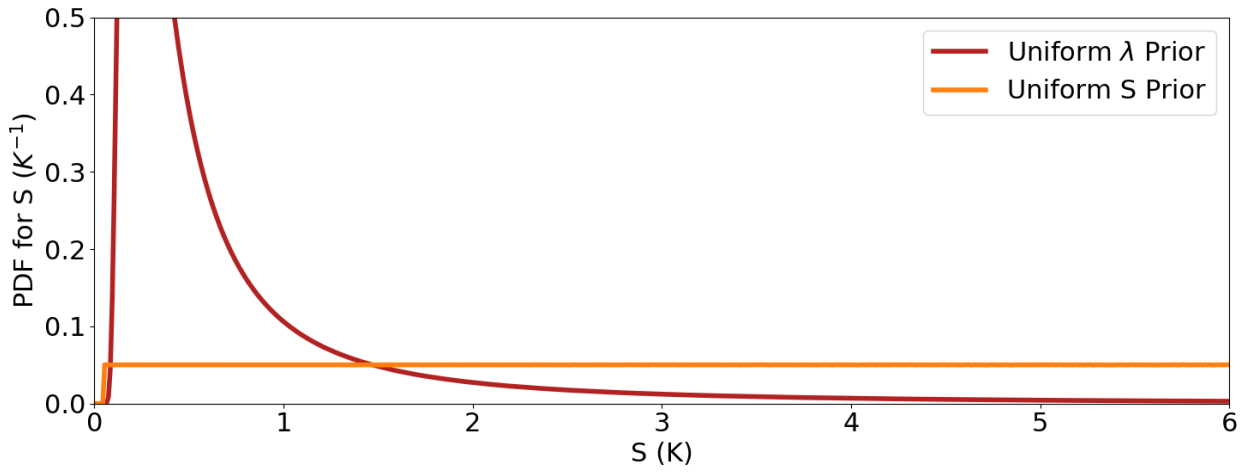
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**Figure 20** . Posterior PDF for  $S$  and comparison of lines of evidence. Panel (a) shows our Baseline posterior PDF for  $S$  in black, and PDFs for each main line of evidence individually, where the process evidence is combined with a uniform  $\lambda$  prior while the others are combined with a uniform prior on  $S$ . (b) shows marginal likelihoods for  $S$  for the various lines of evidence used in the Baseline calculation: the individual-feedback process evidence (section 3); the likelihood from historical evidence (section 4); and the likelihoods for past warm and cold climates from paleoclimate evidence plus their combined likelihood (section 5). All likelihoods are scaled to have a maximum value of unity. Vertical grey lines show the 66% range for the Baseline posterior for  $S$ .

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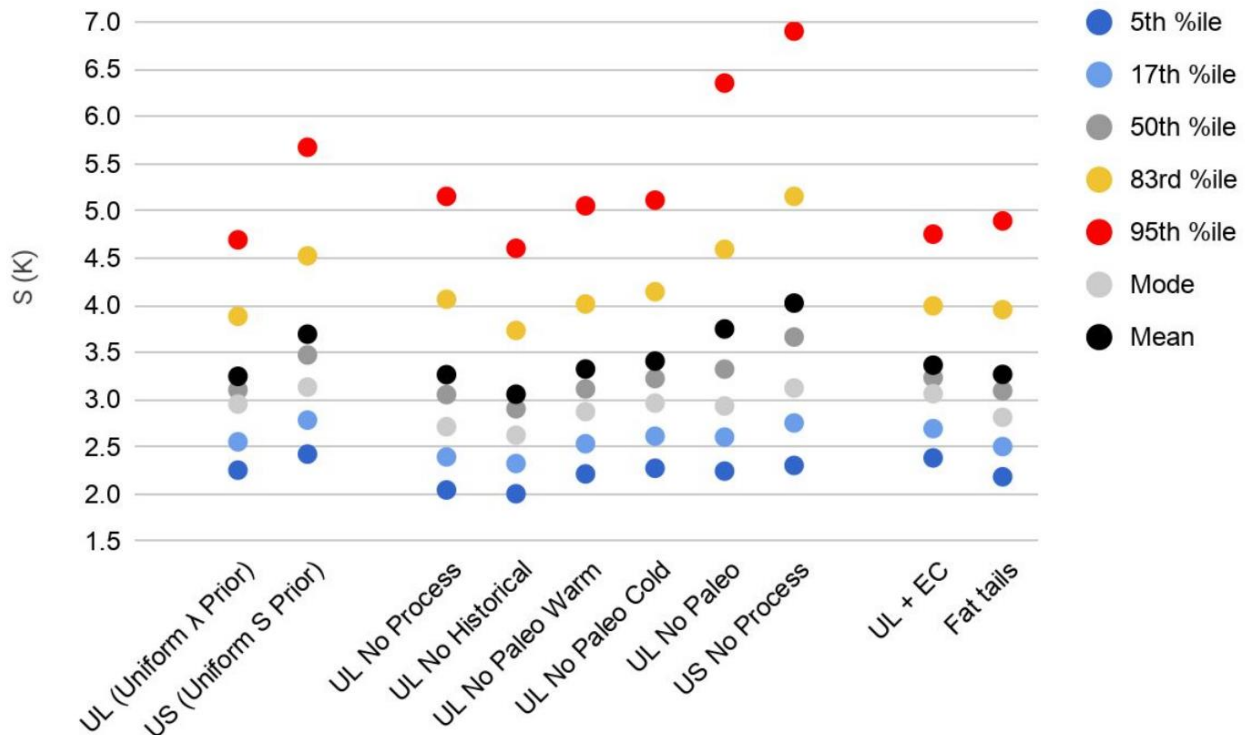


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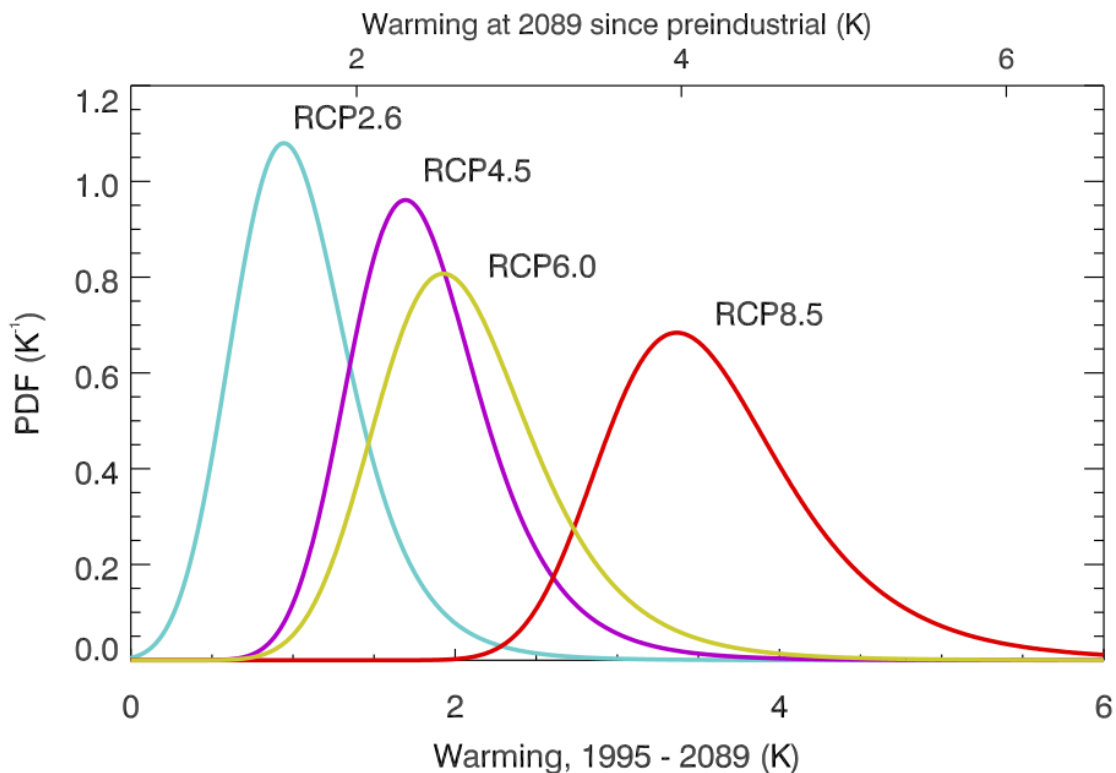
**Figure 21** . Prior predictive distributions for (a)  $\lambda$  and (b)  $S$ . Our Baseline (UL, red) prior is uniform in six  $\lambda_i$  feedbacks, each  $\sim U(-10, 10) \text{ W m}^{-2} \text{ K}^{-1}$ , compared to an alternative prior (US, orange) which reweights the Baseline prior to be uniform in  $S$  from near 0 to 20  $\text{K}$ .



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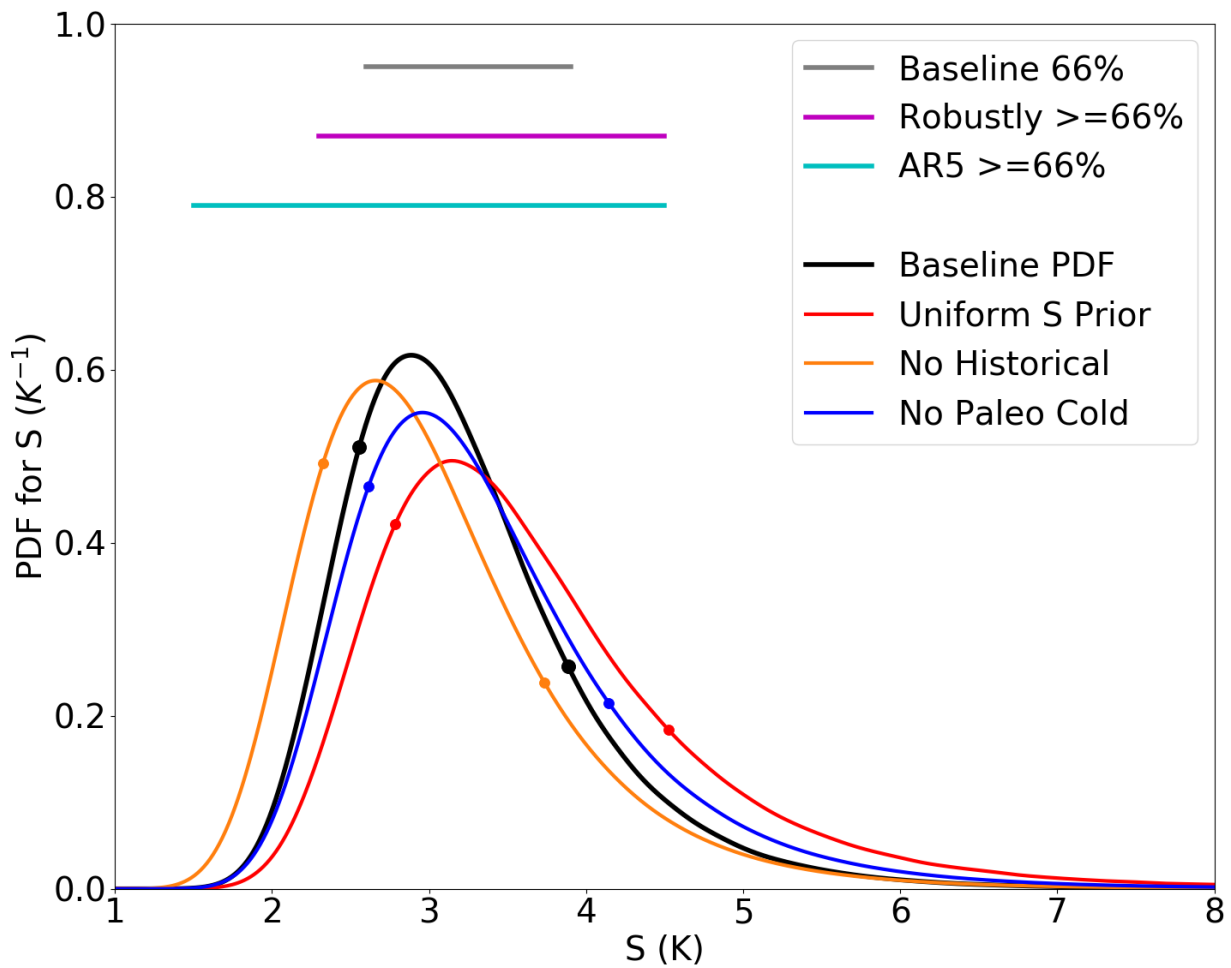
**Figure 22.** Graphical summary of statistics of posterior PDFs for  $S$ . UL is the Baseline calculation with a uniform prior on  $\lambda$  and US has a uniform prior on  $S$ . The middle group shows the effect of removing various lines of evidence in turn. UL + EC shows the impact of including the effect of emergent constraints. The effect of substituting fat-tailed distributions for some lines of evidence is also shown for the Baseline case.

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**Figure 23** . PDFs of the warming by late this century, from our Baseline PDF of  $S$ . These warming PDFs are obtained by converting  $S$  to warming using the best linear fit, then convolving the induced PDF with Gaussian uncertainty, as shown by the shading in Fig. 1b. Results from RCP6.0 employ data from Forster et al. (2013). Note that the warming is calculated relative to 1985–2005; approximate warming relative to pre-industrial is shown at the top, based on 0.6 K warming having occurred by 1985–2005. Warming was estimated using the difference of 20-year means centered on the years 1995 or 2089.



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 6322 **Figure 24.** PDFs of  $S$  in comparison with AR5. The Baseline PDF is shown in black, and its  
 6323 66% range (2.6-3.9 K) in grey. Colored curves show PDFs from sensitivity tests which cover a  
 6324 range for  $S$  which could plausibly arise given reasonable alternative assumptions or interpretations  
 6325 of the evidence, summarized by the magenta line (2.3-4.5 K). These are the Baseline case but with  
 6326 a uniform  $S$  prior (red), the Baseline without the Historical evidence (orange) and the Baseline  
 6327 case without the cold paleoclimate evidence (Blue). The 66%-or-greater (“likely”) range from the  
 6328 most recent IPCC assessment (AR5) (1.5-4.5 K) is shown in cyan. Circles indicate 17th and 83rd  
 6329 percentile values.  
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