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## Observational constraints on the effective climate sensitivity from the historical period

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Katarzyna B Tokarska<sup>1,5</sup> , Gabriele C Hegerl<sup>1</sup> , Andrew P Schurer<sup>1</sup> , Piers M Forster<sup>2</sup> and Kate Marvel<sup>3,4</sup><sup>1</sup> School of Geosciences, University of Edinburgh, United Kingdom<sup>2</sup> University of Leeds, United Kingdom<sup>3</sup> NASA Goddard Institute for Space Studies, New York, NY, United States of America<sup>4</sup> Department of Applied Physics and Applied Mathematics, Columbia University, New York, NY, United States of America<sup>5</sup> Current affiliation: Institute for Atmospheric and Climate Science, ETH Zurich, Zurich, SwitzerlandE-mail: [kasia.tokarska@ed.ac.uk](mailto:kasia.tokarska@ed.ac.uk)

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**Keywords:** climate sensitivity, detection and attribution, historical period, greenhouse gasesSupplementary material for this article is available [online](#)**Abstract**

The observed warming in the atmosphere and ocean can be used to estimate the climate sensitivity linked to present-day feedbacks, which is referred to as the effective climate sensitivity ( $S_{hist}$ ). However, such an estimate is affected by uncertainty in the radiative forcing, particularly aerosols, over the historical period. Here, we make use of detection and attribution techniques to derive the surface air temperature and ocean warming that can be attributed directly to greenhouse gas increases. These serve as inputs to a simple energy budget to infer the likelihood of  $S_{hist}$  in response to observed greenhouse gas increases over two time periods (1862–2012 and 1955–2012). The benefit of using greenhouse gas attributable quantities is that they are not subject to uncertainties in the aerosol forcing (other than uncertainty in the attribution to greenhouse gas versus aerosol forcing not captured by the multi-model aerosol response pattern). The resulting effective climate sensitivity estimate,  $S_{hist}$ , ranges from 1.3 °C to 3.1 °C (5%–95% range) over the full instrumental period (1862–2012) for our best estimate, and gets slightly wider when considering further uncertainties. This estimate increases to 1.7 °C–4.6 °C if using the shorter period (1955–2012). We also evaluate the climate model simulated surface air temperature and ocean heat content increase in response to greenhouse gas forcing over the same periods, and compare them with the observationally-constrained values. We find that the ocean warming simulated in greenhouse gas only simulations in models considered here is consistent with that attributed to greenhouse gas increases from observations, while one model simulates more greenhouse gas-induced surface air warming than observed. However, other models with sensitivity outside our range show greenhouse gas warming that is consistent with that attributed in observations, emphasising that feedbacks during the historical period may differ from the feedbacks at CO<sub>2</sub> doubling and from those at true equilibrium.

**1. Motivation**

The ultimate warming of the climate system in response to a doubling of atmospheric CO<sub>2</sub> concentration from preindustrial, and once the system reaches an equilibrium, is known as the equilibrium climate sensitivity (ECS), and is likely to range from 1.5 °C to 4.5 °C (17%–83% probability), as assessed by the Fifth Assessment Report of the Intergovernmental Panel on

Climate Change (IPCC AR5 2013). However, the historical and present-day state of the climate system that we can observe is not at equilibrium yet. The global ocean stores more than 90% of the Earth's energy imbalance, taking centuries to reach equilibrium (Hansen *et al* 2011, Church *et al* 2013). We refer to the climate sensitivity inferred from the historical and present-day conditions as the *effective* climate sensitivity ( $S_{hist}$ ), which may be different from climate

sensitivity at equilibrium (Knutti *et al* 2017, Rugenstein *et al* 2019), due to slow response additional climate feedbacks that come into play on longer time-scales and when the pattern of global warming is fully developed (including, for example, sea ice retreat). (Note that the Earth system sensitivity that includes the response to ice sheet melt and release of CO<sub>2</sub> from permafrost may be even higher; Knutti *et al* 2017.) Furthermore, the strength of some feedbacks, such as the cloud feedback, may change over time and at higher levels of warming (Knutti *et al* 2017, Dessler and Forster 2018). Nevertheless, observations during the historical period (here defined as 1862–2012) provide us with useful information, allowing us to constrain important aspects of the climate model responses (Forster 2016, Knutti *et al* 2017).

There are multitudes of estimates of climate sensitivity summarised in Knutti *et al* (2017), many of which are based on estimates of feedbacks and analysis of climate models (summarised in Knutti *et al* 2017—figure 1 therein with red bars: e.g. Harris *et al* 2013, van Hateren 2013, Shindell 2014, Millar *et al* 2015). Other estimates of climate sensitivity arise from observations over the historical period (e.g. Gregory *et al* 2002, Frame *et al* 2005, Otto *et al* 2013, Johansson *et al* 2015, Forster 2016, Lewis 2016, Skeie *et al* 2018, see Knutti *et al* 2017 for a comprehensive summary). Deriving observational constraints on the effective climate sensitivity ( $S_{hist}$ ) from the historical period is challenging due to the uncertainties in radiative forcing, ocean warming, and the role of internal climate variability in long-term change (Gregory *et al* 2002, Otto *et al* 2013, Forster 2016). The resulting  $S_{hist}$  estimates are subject to assumptions about radiative forcing, which are strongly affected by uncertainty in the forcing by anthropogenic aerosols. Also, the observed warming estimates are subject to incomplete coverage, which is especially low in the earlier historical period (Cowtan and Way 2014). In addition, fitting simple climate models to observations as done in Aldrin *et al* (2012) and Johansson *et al* (2015), for example, is subject to uncertainty in those simple models and can be quite sensitive to assumptions (see discussion in Sherwood *et al* in review).

The uncertainty arising from the unknown magnitude of the aerosol forcing in the historical period could be avoided by focusing on the observed warming that has been attributed to greenhouse gases only. Few previous studies (Frame *et al* 2005, Lewis 2016) followed that idea and derived constraints on the effective climate sensitivity by making use of the anthropogenic or greenhouse gas attributable warming, obtained in a detection and attribution analysis. However, these studies did not obtain greenhouse gas attributable ocean heat content in a detection and attribution analysis, using instead the observed ocean heat content estimates to all forcing.

Here, we make use of detection and attribution techniques to quantify both the greenhouse gas

attributable change in surface temperature (using blended surface air and sea surface temperature, for a direct comparison with the observed warming), and ocean heat content. We then apply those results to the planetary energy budget using the forcing-feedback framework (Gregory *et al* 2004, Otto *et al* 2013) to derive observational constraints on the effective climate sensitivity ( $S_{hist_{GHG}}$ ). These results are then compared with an alternative approach of applying observational constraints on future model projections.

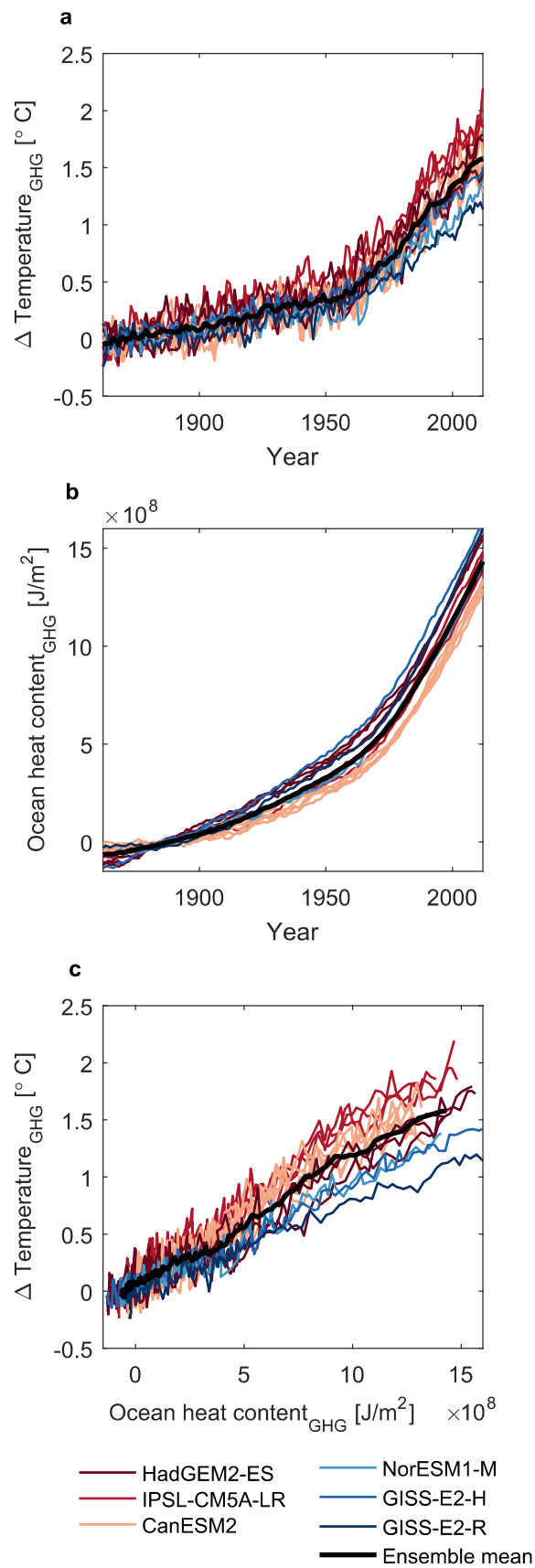
## 2. Methods

### 2.1. Greenhouse gas attributable warming and ocean heat content

To derive the greenhouse gas attributable contributions to the ocean heat content ( $\Delta N_{GHG}$ ) and to temperature ( $\Delta T_{GHG}$ ) we make use of detection and attribution method of regularised optimal fingerprinting (ROF; Ribes and Terray 2013, Ribes *et al* 2013), which is based on a total least squares regression (Allen and Stott 2003). Under the assumption of linear additivity of the forcings (e.g. Hegerl *et al* 1997, Tett *et al* 1999, Gillett *et al* 2004, Swart *et al* 2018), the true observed climate response ( $y^*$ ) can be expressed as a sum of the models' noise-free responses to individual forcings ( $x^*_i$ ), scaled by respective scaling factors ( $\beta_i$ ) (equation (1)). This method accounts for noise due to internal variability in observations  $\varepsilon_y$ , and noise  $\varepsilon_{x_i}$  in the model response due to internal variability and a finite ensemble size for each noise-free modelled response ( $x^*_i$ ) (Ribes *et al* 2013):

$$y^* = \sum_{i=1}^l \beta_i x^*_i \quad (1)$$

The scaling factors ( $\beta_{GHG}$ ) for the ocean warming were derived in the same way as in Tokarska *et al* (2019) (based on the period 1955–2012, due to available observational coverage), for the set of models considered here (supplementary table S1, available online at [stacks.iop.org/ERL/15/034043/mmedia](https://stacks.iop.org/ERL/15/034043/mmedia)). The scaling factors for surface warming were derived using the models' surface warming as a blended product of surface air temperature and the sea surface temperatures, for consistency with the observations (HadCRUT4.5; Morice *et al* 2012), as in Schurer *et al* (2018), following Cowtan *et al* 2015, for the period 1862–2012. In both cases (for ocean warming and surface warming), the models' responses were calculated in the same way as observations, and masked according to the observational coverage at each time step, to allow for a like-to-like comparison of models and observations, prior to the detection and attribution. Prior to masking, model output was re-gridded by bilinear interpolation onto the respective observational grids, and on the common depth layers (in case of ocean warming). In the energy budget analysis that follows in the results section (section 3.3), we make use of full coverage of model simulated responses in



**Figure 1.** Time-series of model responses to greenhouse gas forcing: surface temperature (a), and ocean heat uptake at 0–2000 m (b). Panel (c) shows the relationship between the top two panels: surface air temperature as a function of ocean heat content (in response to greenhouse gas forcing alone). Note: All panels show responses to greenhouse gas only (GHG) forcing, based on CMIP5 models (as labelled) in historical GHG-only simulations. Higher ECS models are indicated by red, while lower ECS models are indicated in blue (supplementary table S1). Surface air temperature is shown with respect to the 1862–1880 period.

greenhouse gas only historical simulations in order to avoid low bias due to missing values (Benestad *et al* 2019), multiplying the model simulated space-time patterns by the range of the  $\beta_{GHG}$  scaling factors that are consistent with observed changes.

We carried on the detection and attribution (ROF) analysis on different sets of inputs, summarised in supplementary table S2. (The detection and attribution analysis is described in detail in Tokarska *et al* (2019) and follows the Ribes *et al* (2013) approach.) We use also historical simulations driven by natural-only and greenhouse gas-only forcings that extend to the year 2012. The historical all-forcing simulations were obtained either using the extensions (until the year 2012) or extended by the first few years from RCP 4.5 simulations (for the period 2006–2012).

Internal variability is considered in detection and attribution, and its effect is included in the uncertainty ranges of the scaling factors. In order to estimate the sensitivity of results to uncertainty in estimates of internal variability we also use detection and attribution results where the noise due to internal variability was doubled by increasing the variance (in the noise from the control runs) by a factor of two (as in Tokarska *et al* 2019).

## 2.2. Greenhouse gas attributable effective climate sensitivity ( $S_{histGHG}$ )

The ECS is determined by atmospheric feedbacks to increases in greenhouse gases, (see definition above). In models, it is usually derived from simulations of greenhouse warming at equilibrium or in response to a large abrupt forcing (i.e. high signal-to-noise ratio; Marvel *et al* 2018). It has been recognised that the feedbacks to an early and increasing warming of the climate system in response to increasing greenhouse gases may not be identical to those to equilibrated greenhouse warming. Also, feedbacks are influenced by spatial patterns of warming (Knutti *et al* 2017, Andrews *et al* 2018), which means that the effective climate sensitivity during the historical period may be different from that at equilibrium. Therefore, if derived from the historical period, ECS is referred to as the *effective* climate sensitivity (Gregory *et al* 2004, Otto *et al* 2013, Forster 2016), and can be expressed as  $S_{hist}$  in equation (2):

$$S_{hist} = \frac{F_{2 \times CO_2} \Delta T}{\Delta F - \Delta N}, \quad (2)$$

where  $F_{2 \times CO_2}$  is the radiative forcing to CO<sub>2</sub> doubling (quantified in a standard 1% per year CO<sub>2</sub> increase experiment),  $\Delta T$  is warming in the given historical period,  $\Delta F$  is the radiative forcing estimate, and  $\Delta N$  is the net energy imbalance, dominated by the ocean heat uptake (Rhein *et al* 2013).  $S_{hist}$  in equation (2) is equal to the ECS only if the feedbacks that determine it (often characterised by a parameter in an energy budget equation) are the same at present as at equilibrium.

This energy budget considers the total effective radiative forcing over the historical period, whose largest uncertainty is due to the uncertainty of aerosol forcing: aerosols cause cooling, which may mask out some of the warming caused by greenhouse gases. Here we aim to avoid aerosol uncertainty by making use of the atmospheric and ocean warming that has been attributed to greenhouse gases alone (dominated by CO<sub>2</sub> radiative forcing). Hence, based on equation (2), we define the effective climate sensitivity due to greenhouse gas-attributable response as  $S_{histGHG}$ , expressed by equation (3):

$$S_{histGHG} = \frac{F_{2 \times CO_2} \Delta T_{GHG}}{\Delta F_{GHG} - \Delta N_{GHG}}, \quad (3)$$

where  $\Delta F_{GHG}$  is the greenhouse gas effective radiative forcing for the analysis period. Both the greenhouse gas attributable warming ( $\Delta T_{GHG}$ ) and the greenhouse gas attributable ocean heat content change ( $\Delta N_{GHG}$ , representing the net energy imbalance) and their respective uncertainties in the greenhouse gas attributable responses are obtained by scaling the model responses in surface air temperature and ocean heat content by the corresponding scaling factors  $\beta_{GHG}$  derived in a detection and attribution analysis (see section 2.1 and supplementary tables S2 and S3).

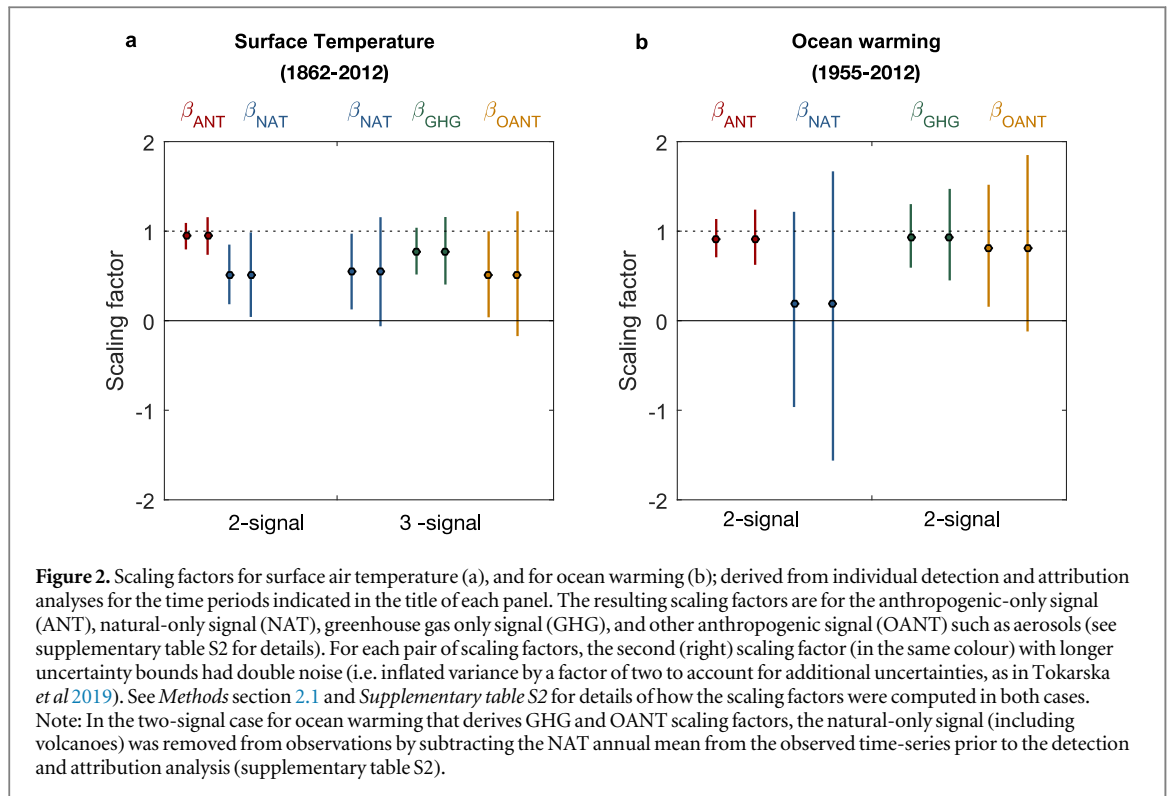
In section 3.3, we compute probability density distributions of  $S_{histGHG}$  in two following ways. First, we calculated  $S_{histGHG}$  directly by drawing random samples from Gaussian distributions (or joined half-Gaussian, if the 5%–95% attributed range was not symmetric; supplementary figure S1) of all the parameters on RHS of equation (3). (See Supplementary tables S1 to S4 for details, and supplementary figure S1 illustrating the input distributions.) The spread for of  $\Delta T_{GHG}$  comes from the uncertainty range in the  $\beta_{GHG}$  scaling factors times the model simulated change, replicating the fit to observations (figure 2). However, this direct approach of obtaining  $S_{histGHG}$  is subject to an implicit prior on  $S_{histGHG}$  which may be biasing the distribution towards lower  $S_{histGHG}$  values by under-sampling high  $S_{hist}$  values (Frame *et al* 2005).

To evaluate the implications of such an implicit prior on  $S_{histGHG}$ , we also took an alternative approach (Sherwood *et al* in review), where we assume a flat uniform prior on  $S_{histGHG}$  and then calculated the expected warming  $\Delta T_{expGHG}$  given the ranges of  $\Delta F_{GHG}$ ,  $\Delta N_{GHG}$ , and  $F_{2 \times CO_2}$ , by re-arranging equation (3) into a forward model. For a putative value of  $S_{histGHG}$ , the expected temperature is:

$$\Delta T_{expGHG} = S_{histGHG} \frac{\Delta F_{GHG} - \Delta N_{GHG}}{F_{2 \times CO_2}} + \varepsilon, \quad (4)$$

where  $\varepsilon$  is the observational error (including observational uncertainty and unforced climate variability (Sherwood *et al* in review). As before, the inputs  $\Delta F_{GHG}$ ,  $\Delta N_{GHG}$ , and  $F_{2 \times CO_2}$  are sampled from corresponding Gaussian or joined half-Gaussian (if not symmetric) distributions using the random sampling approach (i.e. drawing random samples from the





input distributions), but  $\Delta T_{exp_{GHG}}$  in equation (4) is evaluated for  $S_{hist_{GHG}}$  values ranging from 0 to 10 K, sampling a uniform prior. (We also performed sensitivity to the choice of a different range of the prior 0 °C to 5 °C, and 0 °C to 20 °C, which does not influence our results to first decimal place).

The resulting expected warming ( $\Delta T_{exp_{GHG}}$ ) can be then evaluated against the observationally-constrained greenhouse gas attributable warming ( $\Delta T_{OBS_{GHG}}$ ), allowing us to derive the likelihood of  $S_{hist_{GHG}}$ , and its corresponding posterior probability density. The likelihood of  $S_{hist_{GHG}}$  is calculated by evaluating the distance for each of the random samples of expected warming ( $\Delta T_{exp_{GHG}}$ ) to the greenhouse gas attributable warming ( $\Delta T_{OBS_{GHG}}$ ). To avoid summing extremely low density values, we considered only density values which fall within  $3\sigma$  of the mean value of  $\Delta T_{exp_{GHG}}$ , which were then aggregated for each corresponding  $S_{hist_{GHG}}$  value, resulting in the likelihood distribution for  $S_{GHG}$ .

This likelihood  $P(T_{OBS_{GHG}}|S_{hist_{GHG}}, \Delta N_{GHG}, \Delta F_{GHG}, \Delta F_{2 \times CO_2})$  quantifies how likely the observation-based greenhouse gas attributable warming  $\Delta T_{OBS_{GHG}}$  would be, given the expected ranges of  $\Delta F_{GHG}$ ,  $\Delta N_{GHG}$ , and  $F_{2 \times CO_2}$  and considering all plausible values of  $S_{hist_{GHG}}$  (expressed by the flat prior) (as in Sherwood *et al* in review). Since the prior  $S_{hist_{GHG}}$  distribution  $P(S_{hist_{GHG}})$  is represented by a flat prior, the posterior distribution  $P(S_{hist_{GHG}}|T_{OBS_{GHG}}, \Delta N_{GHG}, \Delta F_{GHG}, \Delta F_{2 \times CO_2})$  is then the likelihood distribution normalised to a unit area. Supplementary table S3 contains the values of parameters used in the two different distributions discussed in section 3.3.

### 3. Results

#### 3.1. Surface air temperature and ocean heat content in GHG-only simulations

Both surface air temperature and ocean heat content continually increase in the historical period in response to greenhouse gas forcing in historical greenhouse gas only simulations (figures 1(a), (b)). As a result, there is an approximately linear relationship between the greenhouse gas attributable temperature and ocean heat content, shown in figure 1(c). We make use of this emergent property of the climate system in response to greenhouse gases alone later in section 3.4 to provide observational constraints on the historical greenhouse gas attributable responses. (Note that models with high atmospheric warming do not necessarily have larger increases in ocean heat content, for the periods considered here.)

#### 3.2. Adjustments to greenhouse gas attributable responses

To derive the observationally-constrained greenhouse gas attributable surface air temperature and ocean warming, we performed a detection and attribution analysis (Methods section 2.1). The resulting scaling factors (figure 2) were derived separately for the surface air warming (based on HadCRUT4.5 observations) and ocean warming (based on the Levitus *et al* 2012 dataset, and following the methodology in Tokarska *et al* 2019), as specified in Supplementary table S4. In the detection and attribution analysis (following Ribes *et al* 2013 and Tokarska *et al* 2019), the scaling factors were obtained by regressing the

observations onto model response patterns (Methods section 2.1; supplementary table S2). The scaling factors and their uncertainty range resulting from the attribution analysis indicate how much the modelled response to each forcing needs to and can be adjusted to reconstruct the observations (Methods, section 2.1).

Our results show that for both, surface air warming (in the 1861–2012 period) and ocean warming (in the 1955–2012 period), the best estimate greenhouse gas only response is well constrained and can be separated from natural and other anthropogenic responses for surface temperature (figure 2), and from other anthropogenic factors for ocean warming, with natural forcing estimated to have only a small influence (see Tokarska *et al* 2019). The greenhouse gas response is found to be slightly smaller in the multi-model mean than in observations, and thus is adjusted slightly downward ( $\beta_{GHG}$  scaling factors less than 1; figure 2), but this adjustment is not significant (error bars consistent with no adjustment, i.e. scaling factor consistent with 1; figure 2). Next, we make use of the  $\beta_{GHG}$  scaling factors, applied to the greenhouse gas only time-series (figure 1), to calculate the observationally-constrained greenhouse gas attributable responses for the historical period (supplementary tables S2, S3), and the resulting effective climate sensitivity  $S_{hist_{GHG}}$ , in section 3.3. Note that figure 2 shows for comparison also scaling factors for anthropogenic combined warming which are not used in this study, but they show that the attribution results are robust between signal combinations.

### 3.3. Energy budget approach to the greenhouse gas attributable effective climate sensitivity

The greenhouse gas-attributable responses (figure 1), scaled by the respective  $\beta_{GHG}$  scaling factors to better match the observations (figure 2; Methods section 2.1), allow us to derive a probability distribution for the observationally-constrained, greenhouse gas attributable, effective climate sensitivity  $S_{hist_{GHG}}$ . We make use of the energy budget equation (equation (2)), using the following two approaches: (1) a direct sampling approach (Methods, equation (3)), and a ‘forward model’ approach (Methods, equation (4); flat prior in  $S_{hist_{GHG}}$ ).

We carried on analysis on two different periods: 1862–2012 (Case A) and for 1955–2012 (Case B), with inputs described in supplementary table S3. In this section, case names with number ‘1’ (i.e. A1, B1) have regular noise, and case names with number ‘2’ (i.e. A2, B2) have doubled the noise (by doubling the variance obtained in the control-run simulations) prior to detection and attribution. Such inflating of the noise results in wider uncertainty ranges of the scaling factors, and wider overall uncertainty ranges. This factor has been estimated as approximately correcting for the uncertainty of using the multi-model mean response

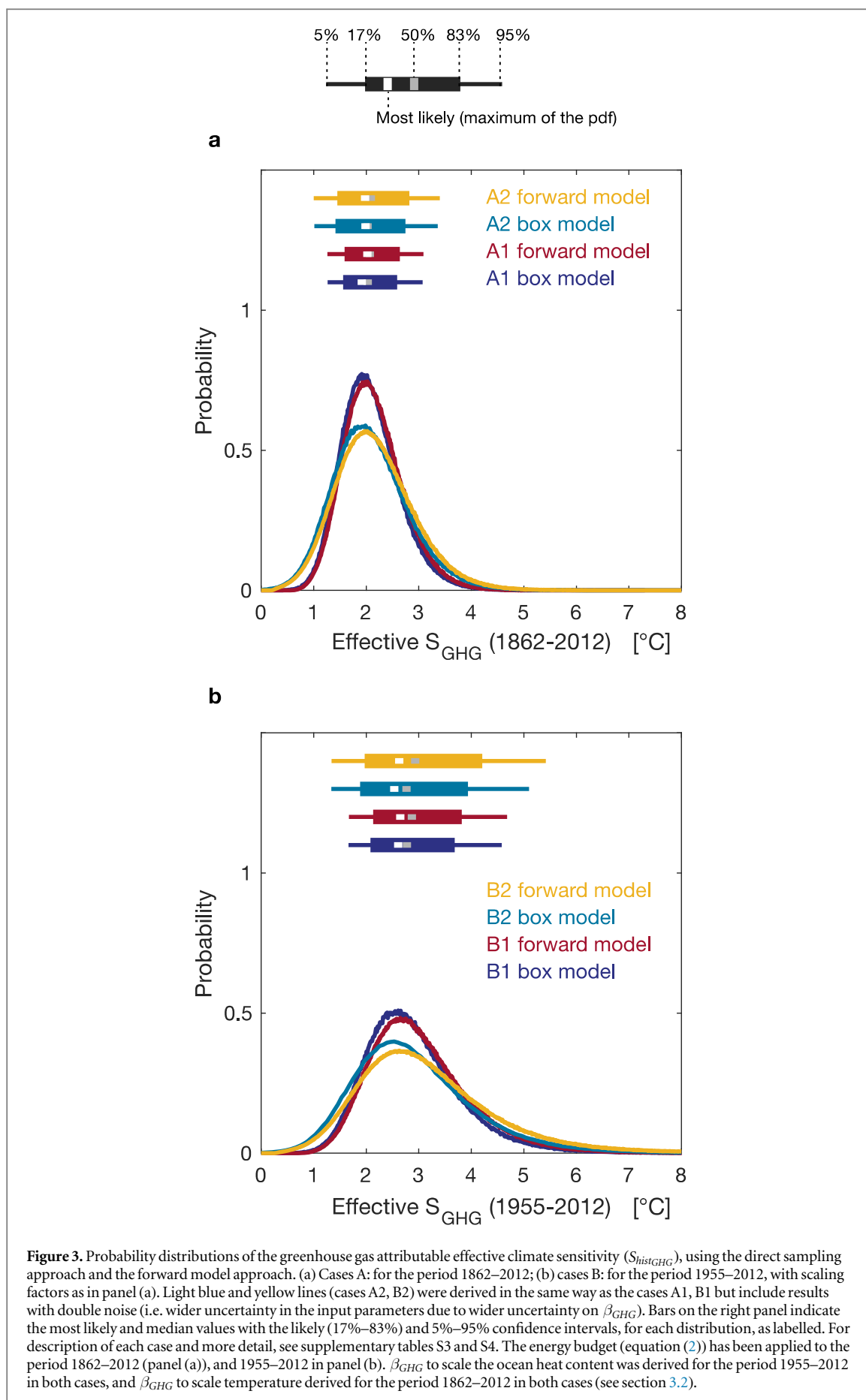
instead of fully accounting for climate model response pattern uncertainty (Schurer *et al* 2018).

We assume that the scaling factors  $\beta_{GHG}$ , which describe the strength of the modelled response to forcing, are constant through time. We calculate the scaling factors for surface temperature and ocean heat content using the longest period available (as in figure 2). We then apply those scaling factors to the two different time periods: 1862–2012 (case A), and 1955–2012 (case B). Specifically, the scaling factor  $\beta_{GHG}$  ocean heat content was derived for the period 1955–2012 only, as earlier observations are not available, and is applied to ocean heat content changes in climate models across the full analysis period time periods in each case (case A that covers 1862–2012 period, and case B that covers 1955–2012 period). Similarly, the scaling factor  $\beta_{GHG}$  for surface air temperature was derived for the period with longest observational data available (i.e. 1862–2012), and is applied in both cases A and B of the analysis here.

The resulting probability distributions from random sampling of the observationally-constrained greenhouse gas attributable responses (Methods, section 2.2), yield an estimate of the greenhouse gas attributable effective climate sensitivity ( $S_{hist_{GHG}}$ ) for the period 1862–2012 (case A) that ranges from 1.3 °C to 3.1 °C (5%–95% interval with the most likely value at 1.9 °C, and median of 2.0 °C; figure 3; ‘Box model’ case A1) using the direct sampling approach, and from 1.3 to 3.1 °C (5%–95% interval with the most likely value at 2.0 °C, and median 2.1 °C; figure 3(a); ‘Forward model’ case A1). Using the ‘forward model’ approach which is based on an explicit flat prior on ECS hence shows only small sensitivity to the prior information used (supplementary table S4). However, using the a different period 1955–2012 (case B) results in higher values of  $S_{hist_{GHG}}$ , with the median 2.8 °C, most likely value 2.6 °C, and the 5%–95% range of 1.7 °C–4.6 °C (figure 3(b); case B1 Box model, supplementary table S4). The uncertainty bounds are wider in case B, compared to case A, showing that the observational constraint from the shorter period is weaker. Using the longer period also results in better constrained greenhouse gas attributable warming. Using double-noise in  $\beta_{GHG}$  factors (figure 2), and sampling from the resulting inflated Gaussian distribution yields  $S_{hist_{GHG}}$  that also have wider uncertainty bounds (Cases A2, B2, figure 3, supplementary table S3 and S4).

Our estimate of  $S_{hist_{GHG}}$  is lower than the documented ECS of some climate models (e.g. CMIP5 multi-model mean ECS of 3.22 °C; Forster *et al* 2013), including that of some used in the analysis (see supplementary table S1). However, it is well understood that time-dependent feedbacks might render  $S_{hist_{GHG}}$  lower than  $S$  at equilibrium (Knutti *et al* 2017, Andrews *et al* 2018). Furthermore, different ways of calculating ECS in climate models results in different values, which are





often lower than the true ECS when using equilibrated simulations (Rugenstein *et al* 2019).

Such lower values for  $S_{hist_{GHG}}$  than  $S$  at equilibrium can be explained by the effects of changing strength of the feedbacks at higher levels of warming (Knutti *et al* 2017). The climate feedback parameter (defined as  $1/S_{hist}$ ) has been shown to vary in the historical period (Gregory and Andrews 2016, Andrews *et al* 2018), and depends on both time-variation and the forcing agent. Andrews *et al* 2018 show that the feedback parameter ( $1/S_{hist}$ ) is decreasing, particularly after 1940s onwards (Andrews *et al* 2018; figure 2(f) therein). This would suggest increase in  $S_{hist}$  during that period. Potential changes in feedbacks are neglected if assuming that  $S_{hist}$  is equal to  $S$  (at equilibrium), an assumption often made if inferring  $S$  using simple climate models with constant feedbacks. Our tighter and lower values for  $S_{hist_{GHG}}$  may be affected by this effect, but may alternatively also reflect better constraints with a longer time horizon, or be affected by uncertainties in the early record we can not fully quantify. For example, an uncertainty in the long period is that it effectively uses extrapolation of the observational constraint from the second half of the 20th century to the full analysis period, which may introduce error particularly if some model simulations are affected by drift in the ocean. Also, analysis periods can matter both due to effects of internal climate variability and possibly residuals from responses by other forcings that may have been not fully separated in the attribution analysis.

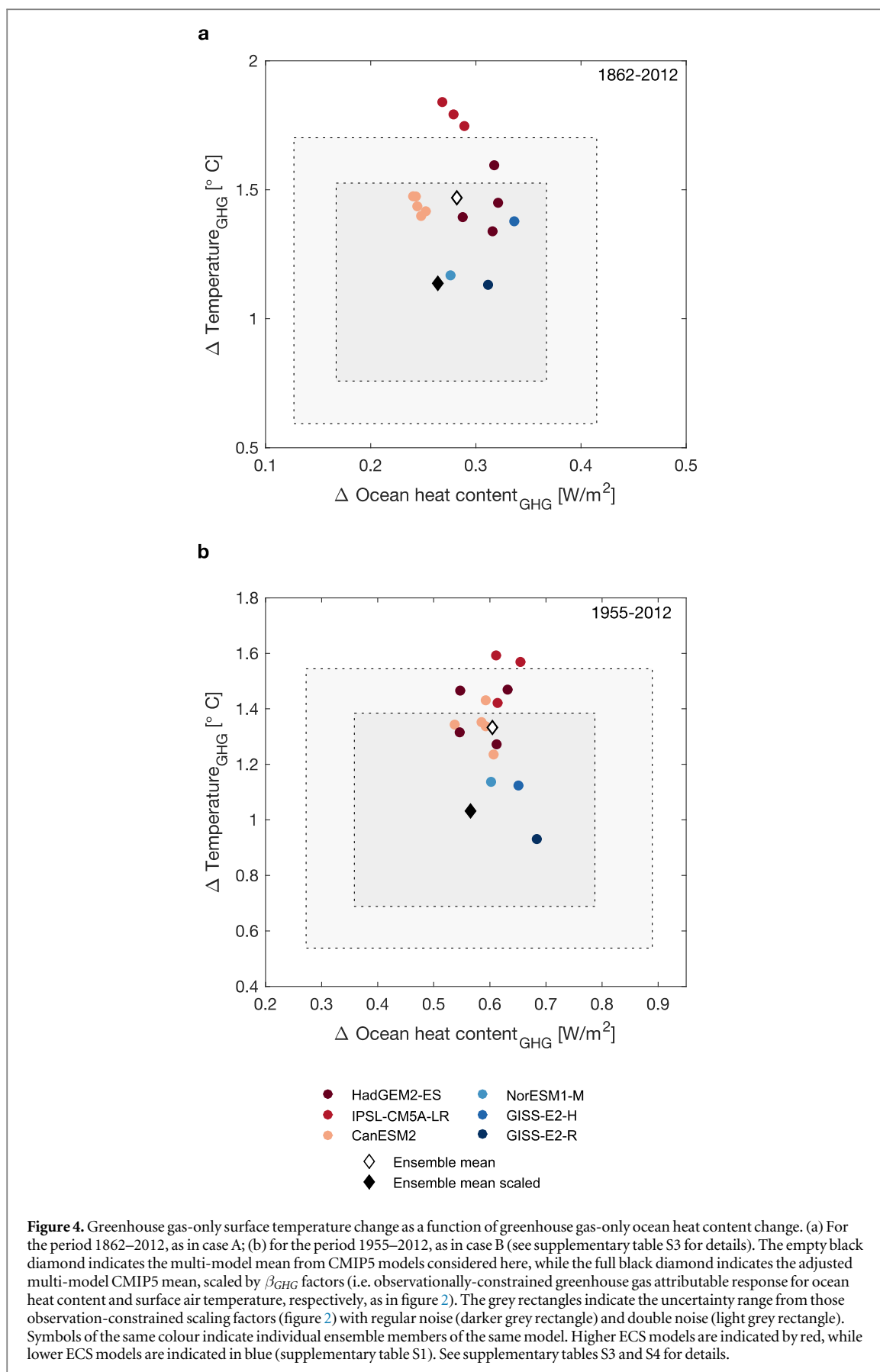
The increased greenhouse gas scaling factors, and with it the increase in estimated effective climate sensitivity calculated from the recent period (1955–2012) could reflect feedbacks associated with a rapid increase in greenhouse gas forcing. Gregory *et al* (2019) also find that the effective climate sensitivity is higher since the year 1975 when greenhouse gas forcing has rapidly increased. Alternative approaches have been also suggested to this simple energy balance model (equation (2)) that account for stratospheric adjustments, which are related to the changing feedback parameters (Ceppi and Gregory 2019).

### 3.4. Observational constraints on the climate model responses

In this section we use the attributed greenhouse warming in atmosphere and ocean to directly evaluate the model simulated greenhouse gas response. This is to address the problem that time-dependent feedbacks might render  $S_{hist_{GHG}}$  lower than  $S$  at equilibrium, as discussed above section 3.3. The analysis presented here allows us also to evaluate if the rate of heat entering the ocean instead of warming the atmosphere is correct in models. There could be a trade-off between ocean warming and surface warming (for example, some climate models may be very sensitive and show too high ECS, yet mix heat rapidly into the

ocean over the historical period, resulting in surface warming that resembles observations). In order to evaluate if such a trade-off exists, we plotted the greenhouse gas attributable surface temperature change (i.e. greenhouse gas only multi-model mean scaled by the  $\beta_{GHG}$  scaling factor that results in an observationally-constrained quantity) against the greenhouse gas attributable ocean heat content (also multi-model mean scaled by the respective  $\beta_{GHG}$ ), which serve as an observational constraint. We then compare these observationally-constrained ranges with each ensemble member of the historical greenhouse gas only simulation for the models considered here. The observed attributable trend was arrived at by adjusting the multi-model mean from CMIP5 models considered here (figure 4; black empty diamond) by  $\beta_{GHG}$  factors (for ocean and surface air temperature, respectively, as in figure 2), and is shown as the black full diamond. Grey rectangles indicate uncertainty range based on  $\beta_{GHG}$  scaling factors given model internal variability noise (smaller square), and doubled noise in input parameters (larger square; Methods section 2.1). For simplicity, we assume no dependence between ocean and atmospheric warming estimates (note that as the corners of the rectangles are not populated in our examples, this simplification is not important here).

If a model's true forced signal (i.e. its well estimated ensemble mean) falls within the grey rectangles, such model's greenhouse gas response in both ocean and atmosphere is considered to be consistent with the observed greenhouse gas attributable surface air and ocean warming individually. Based on this simple selection, our results suggest that almost all climate models considered here are within the observationally-constrained greenhouse gas attributable ocean warming. Figure 4 also shows that the models spread in their simulated surface air and ocean warming in response to greenhouse gas forcing, but there is no indication of a correlation of points across the two axes, suggesting that the independent treatment of both constraints here is reasonable, and that there are no models that hide strong sensitivity through stronger ocean warming or that show weak warming compensated by lack of ocean heat uptake. Of the three models with ECS values outside our  $S_{hist_{GHG}}$  values (3.4 °C as the 95th percentile in A2 forward model case, figure 3(a); for the longer analysis period 1862–2012), indicated in red in figure 4(a) (see supplementary table S1 for climate sensitivity values), two are clearly consistent with the observed greenhouse gas signal in atmosphere and ocean in figure 4 (i.e. are within the grey rectangle), emphasising the importance of changing feedbacks with time in these models. In the case of one model with climate sensitivity exceeding 4 °C, however, all individual greenhouse gas simulations are outside even the narrower grey rectangle, suggesting that this model warms too much in surface temperature to be consistent with the



attributed greenhouse gas warming. Figure 4 illustrates that the multi-model-ensemble mean in response to greenhouse gas forcing is encompassed by the observationally-constrained rectangles.

### 3.5. Sources of uncertainty

The detection and attribution analysis used in this study assumes linear additivity of the forcings, which has been shown to be a reasonable assumption both for surface warming (Hegerl *et al* 1997, Tett *et al* 1999, Gillett *et al* 2004), and ocean warming (Swart *et al* 2018). Also, since we make use of the multi-model mean in the inputs for the detection and attribution, our resulting scaling factors may be over-confident (Schurer *et al* 2018). We have addressed this, at least to some extent, by doubling the noise due to internal variability in preindustrial control simulations that are used for the noise estimate (prior to detection and attribution; as in Schurer *et al* 2018), which resulted in wider uncertainty ranges on the scaling factors (figure 2, see Tokarska *et al* 2019 for more detail) that translate to wider uncertainty ranges in the input Gaussian distributions (supplementary figures S1 and S2). Since fewer models are used in this analysis than in Tokarska *et al* 2019, the scaling factors  $\beta_{GHG}$  for the ocean have larger uncertainty bounds than if using more models.

Assumptions about the priors are crucial in probabilistic estimates of climate sensitivity (Frame *et al* 2005), and our choice of parameters is indicated in Supplementary table S3. For simplicity, in the energy budget equation (equation (3)), we assume that all the heat storage occurs in the ocean ( $\Delta N_{GHG}$  component), as the ocean dominates the planetary heat storage (Rhein *et al* 2013), and is based only on the top 2000 m of ocean depths. Taking these two assumptions into account (land heat storage contribution and CO<sub>2</sub> co-dependent in radiative forcing terms) does not have much impact on the resulting ECS likelihood distribution (Sherwood *et al* in review). Also, we did not separate the CO<sub>2</sub> radiative forcing contributions in the  $F_{2 \times CO_2}$  and  $\Delta F_{GHG}$  components, thereby assuming that they are independent, though CO<sub>2</sub> is a component of the greenhouse gas forcing radiative forcing  $\Delta F_{GHG}$ .

## 4. Discussion and conclusions

A simple zero-dimensional energy balance model (equation (2)) provides a straightforward way of estimating the historical and present-day effective climate sensitivity ( $S_{hist}$ ) by sampling observed quantities, such as surface air warming and ocean heat content, within their uncertainty range. By sampling greenhouse gas attributable observed quantities, we provide an observational constraint on climate sensitivity  $S_{hist_{GHG}}$  as driven by feedbacks over the historical period, which is not subject to uncertainties in the

aerosol forcing. This output distribution of  $S_{hist_{GHG}}$  is only slightly sensitive to using a flat prior in  $S$  versus directly sampling from the input distributions (i.e. differences between the direct sampling approach ‘Box model’ and the ‘Forward model’ approach), and also widens only slightly if considering larger observational uncertainties (i.e. doubling the noise due to internal variability prior to detection and attribution analysis; supplementary figures S1 and S2).

Recently, Tokarska *et al* (2020) found that the recent historical period can provide an observational constraint on simulated warming rates in the future, and that some models with high climate sensitivities are not consistent with the observed warming trends for the recent decades. The approach presented here finds only a weak observational constraint, with only one model being outside the observationally-constrained range, and a few models being close to the edge, suggesting that the greenhouse gas observationally-constrained response is not presently a strong constraint for the future, despite suggesting a narrower range of  $S_{hist_{GHG}}$  than supported by some models. However, uncertainties considered here are different in this approach, with more explicit consideration of uncertainty due to natural forcing and uncertainty in the aerosol forcing, at the cost of a weaker result (i.e. the observationally-constrained range here ends up being wider, thus screening-in more models). Also, the time-period considered here is different, and ends sooner than those considered by Tokarska *et al* (2020).

Our results also suggest that the true ECS is likely to be higher than the effective climate sensitivity inferred from historical observations. We emphasise that dimensions other than global mean temperature rise need to be taken into account when discussing either past or future climate change. Increases in greenhouse gases also lead to changes in other components of the climate system, such as hydrological cycle and carbon cycle changes that may not necessarily scale linearly with the global mean temperature rise.

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## Data statement

Data used in this study is available from the following sources:

CMIP model output is available at: <http://pcmdi9.llnl.gov/>.

Ocean warming data is available at: [https://nodc.noaa.gov/OC5/3M\\_HEAT\\_CONTENT/](https://nodc.noaa.gov/OC5/3M_HEAT_CONTENT/).

Blended-masked HadCRUT4 time-series are available from the corresponding author upon request.

The Regularised Optimal Fingerprinting (ROF) detection and attribution package developed by Aurélien Ribes is available at <https://umr-cnrm.fr/spip.php?article23&lang=fr>.

## ORCID iDs

Katarzyna B Tokarska  <https://orcid.org/0000-0001-8887-8798>

Gabriele C Hegerl  <https://orcid.org/0000-0002-4159-1295>

Andrew P Schurer  <https://orcid.org/0000-0002-9176-3622>

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