

Below is or point by point response to the reviewers. The original reviewer's comments are in black and our response in blue. Our comments added after the authors response to the reviewers were published online (March 2018) are in green.

### **Anonymous Referee #1**

The paper "Climate sensitivity estimates - sensitivity to radiative forcing time series and observational data" (by R.B. Skeie, T. Berntsen, M. Aldrin, M. Holden, and G. Myhre) is a sensitivity study on the use of different observational datasets to infer estimates of the effective climate sensitivity using an energy balance model in a Bayesian framework. The paper is essentially a refinement of the results of a previous publication, including a systematic analysis of how the use of different data sources impacts the estimates obtained with the model. The paper is of interest from a methodological point of view. The presentation of the methods and of the results is however very confusing. Overall the paper is suited for publication in Earth System Dynamics, after a substantial revision of the presentation of the methodology and of the results.

The authors employ an energy balance climate/upwelling diffusion ocean model, giving as output the surface temperature in the two hemispheres and the global ocean heat content. The model is combined with a stochastic model representing long and short term variability as well as model errors. The equilibrium climate sensitivity is a parameter of the deterministic model, and is constrained by observations in a Bayesian inference. The authors use several observational datasets, including radiative forcings, global surface temperatures, and ocean heat content, performing a fairly systematic analysis of the role of each data source in determining the final results.

The authors have used the same method in a previous publication (Skeie & al 2014) with partially different data. The estimate of the climate sensitivity and its confidence interval change by 5-10%, remaining well inside the range of values obtained with other methods, including the range given by the IPCC report obtained running complex general circulation models. Such a minor change in the main estimate might question the relevance of the new results. However, the authors show in detail how each of the different datasets included or modified with respect to Skeie & al (2014) contribute to determine the final estimate, and how compensations between changes of different sign lead to an overall small final effect. Particular attention is given to the role of the ocean heat content. The paper is therefore of interest for readers working with this kind of methods. The method has been used previously in other publications and I have no major scientific criticisms, a part from a few questions which I include in a bullet list below.

My main criticism to this paper regards the presentation of the methods and of the results. In order to find informations which are essential to have even a minimal understanding of what the authors describe in the main text, the reader is systematically asked to go back and forth between appendixes, supplementary materials, and the authors' previous publication history. As a result, the paper in its current form is extremely hard to follow. For example, no real description is given of the energy balance model. The reader is referred to Skeie & al (2014) and/or Aldrin & al (2012), and even there the informations are fragmented and partially referring to older publications. And I am not talking about the details of the model. For example, in the description of the model/methods I could not find a qualitative description of how the components of the parameter vector  $\_$  are included in the model. However, some of these parameters are later discussed in the paper, out of the blue for a reader who has not worked with this specific model. This is just an example, there are many others. The same holds for the way the deterministic model is combined with the stochastic terms, and many other aspects of the procedures followed by the authors to obtain their results.

While it is clear that the technical details of the models and of the methodology can (must) be left out of the main text of the paper, in particular if they have been described elsewhere, a minimal but clear and comprehensive description of the models and methods must be present in the paper. To the maximum extent possible, the paper has to be readable stand alone. A similar point holds for the use of appendixes and supplementary materials. They should be used to provide technical details not necessary to follow the flow of the main text, or figures giving complementary informations. Instead, in the way the authors use them, there is no logical difference between figures included in the main text and figures included in the supplementary informations, and in order to understand what the authors have done (again, not the details: the very procedure) it is often necessary to stop reading, move to an appendix, and then come back to to main text. This is extremely confusing, and makes the paper unnecessarily hard to read.

The authors should revise their paper in order to make it clear and readable. A simple but comprehensive description of the models and methods they use that are not standard techniques should be provided. The interplay between the main text and appendixes and supplementary materials should be simplified. That said, I have some more specific remarks which I list below.

There is always a balance between the length of the paper and what must be included in the main text. We can agree with the reviewer that in this case too much has been omitted and put into the appendix, as supplementary material or just referred to previous work.

The data and method section is significantly expanded to include the essential information needed for the readers to be able to understand our method and follow the discussion. Still some of the information has to be retained in the appendices, but we believe the reorganization should satisfy the request from the reviewers. This is described under points 1-3 below.

To simplify the interplay between the main text and the appendices, "Appendix A: Refinement of Skeie14" and "Appendix B: Extending data up to and including 2014" are kept as appendices while the others are merged with the main text. In addition, Figure S2 (the TCR figure) and Figure S6 as well as bottom right panel of Figure S7b are now included in the main text to make the manuscript easier to follow.

1. Page 2, lines 3-6. "Since the current climate is in a non-equilibrium state observationally based methods can only account for the feedbacks operating during the historical period. Thus, these estimates are often referred to as inferred or effective climate sensitivity (Armour, 2017;Forster, 2016) and are generally significantly lower than ECS estimates from Atmosphere-Ocean General Circulation Models (AOGCMs)." Just a comment on this. This is an important remark and I agree with the authors in stressing the difference between "real" equilibrium climate sensitivity and inferred climate sensitivity. Actually, this can be seen rigorously and generally in response theory of dynamical systems. In this framework the ECS can be written as a weighted integral of the imaginary part of linear susceptibility of the system over all frequencies, which implies that one needs all time scales in order to correctly compute the ECS. A similar result holds for transient definitions of the climate sensitivity, like the Transient Climate Response. The authors can find a discussion on this for example in Ragone & al (2016) (equations 9 and 14) and Lucarini & al (2017);

Thank you for pointing at these studies. We will look into this theoretical framework to see how it may be used for our future work.

2. Page 3, lines 1-7. Here it would be good to give a (very) brief description of energy

balance based estimates, of the peculiarities of the method developed by the authors, how they have used it in the past and which results they have obtained, and what the current paper adds to these previous works. This is somehow already done, but it should be more clear and systematic;

We will modify the text to the following:

“In this study we use our estimation model that were first documented in Aldrin et al. (2012) and further developed in Skeie et al. (2014). Our method is more complex than the common energy balance based estimates (Forster, 2016) in that we embed a simple climate model into a stochastic model with radiative forcing time series as input, treating the NH and SH separately and includes a vertical resolution of the ocean (40 layers). The radiative forcing time series are linked to the observations of OHC and temperature change through the simple climate model and the stochastic model, using a Bayesian approach. A unique feature with our method is that we use several observational datasets. The method estimates not only the  $ECS_{inf}$  but simultaneously also provides posterior estimates of the radiative forcing, as well as posterior uncertainty estimates in the observations datasets and correlations between them. In this study we further develop our estimation model with additional observational datasets, including heating rates of the deep ocean (below 700m) and new forcing time series from the IPCC AR5 as well as extended time series from 2010 to 2014 to update our estimate of  $ECS_{inf}$ . We carry out a number of sensitivity experiments to investigate causes of differences in observational based  $ECS_{inf}$  estimates due to differences in the input data (observations of surface temperature, OHC and RF).”

3. Page 3, lines 10-28. The description of the model and methods should be expanded and made clear;

In the model section we have included a paragraph on the SCM before we present  $\mathbf{g}_t = \mathbf{m}_t(\mathbf{x}_{1750:t}, \boldsymbol{\theta}) + \mathbf{n}_t$ . The  $\mathbf{n}_t$  term is then described in more detail (see the response to reviewer 2). At the end of the method section the priors are presented (see response below).

The following section describing the SCM is included:

“The core of our model framework is the SCM, a deterministic energy balance/upwelling-diffusion model (Schlesinger et al., 1992). The SCM calculates annual hemispheric and global mean near-surface temperature change (blended SST and surface air temperature) and changes in global OHC as a function of estimated RF time series. The vertical resolution of the ocean is 40 layers. The output of the SCM can be written as  $\mathbf{m}_t(\mathbf{x}_{1750:t}, \boldsymbol{\theta})$ , where  $\mathbf{x}_{1750:t}$  (the RF from 1750 until year t) and  $\boldsymbol{\theta}$  are the true, but unknown, input values to the SCM.  $\boldsymbol{\theta}$  is a vector of seven parameters, each with a physical meaning. One of these parameters is the climate sensitivity, and other parameters determine how the heat is mixed into the ocean, which includes the mixed layer depth, the air-sea heat exchange coefficient, the vertical diffusivity in the ocean and the upwelling velocity (see Schlesinger et al. (1992) and Aldrin et al. (2012) for details).”

4. Page 3, line 21-23. “Most of the data series are provided with corresponding yearly standard errors. However, these are often small compared to the differences between the data series, indicating that the errors reported by the data providers are too small”. This is an interesting observation by the authors, and I agree with them that in this situation using only one dataset would result in assuming uncertainties that are probably too small. However, to say that data providers provide errors that are too small is quite a statement. If the authors are aware of a discussion in the literature on the statistical non consistency between different datasets of the quantities they refer to, it would be good to be more specific on which datasets are in disagreement with each other and to include some references;

~~We have not seen that this has been discussed in the literature, except that in one of our previous papers. We will present the results from a small analysis where we compare the reported uncertainties with the differences between the corresponding data series, both for temperatures and OHC. This will be included as a table in the supplementary material.~~

After looking more into this, we discovered that the sentence in the manuscript was not correct. The results from Skeie et al. (2014, appendix B) indicated that the reported standard errors for some of the OHC series were too low.

We have replaced:

~~“Most of the data series are provided with corresponding yearly standard errors (Fig. S7). However, these are often small compared to the differences between the data series (Table S2), indicating that the errors reported by the data providers are too small. Therefore, we only use the temporal profiles of the reported errors and estimate their magnitudes within the model.” with~~

“Most of the data series are provided with corresponding yearly standard errors (Fig. S7). However, we only use the temporal profiles of the reported errors and estimate their magnitudes within the model, taking into account the possibilities that the reported standard errors may under- or overestimate the true uncertainty (Appendix A and Aldrin et al., 2012; Skeie et al., 2014).”

In Appendix A we have added a small analysis and a table indicating that the reported observational errors for Levitus, Ishii and Kimoto and ORAS4 (above 700m) series are too low, and the real uncertainty may be larger.

5. Section 2.1. The results about the Transient Climate Sensitivity are actually interesting. If the authors find it possible, I would include them in the main text and discuss them a bit more;

The TCR results are included as an additional panel in Fig. 1 as well as we provide numbers in the main text.

6. Section 3. Forc\_Skeie2014 and Forc\_AR5 have never been defined;

They are defined in table 1, but the definition will now also be included in the main text. In section 2.1 we now include: “The forcing time series are hereafter named Forc\_Skeie2014 and the priors of each forcing mechanisms included (Table S1) are described in detail in the appendix D of Skeie14.”

At the beginning of section 3 we replace the sentence: “We replaced the Forc\_Skeie14 with the AR5 effective radiative forcing (ERF) estimates (Myhre et al., 2013), including the AR5 uncertainties” with “We replaced the Forc\_Skeie14 with the AR5 effective radiative forcing (ERF) estimates (Myhre et al., 2013) hereafter named Forc\_AR5. The priors for the forcing mechanisms included (Table S1) are constructed to be consistent with the uncertainties provided in AR5 and the same relative uncertainty for the prior forcing is used over the entire time period.

We hope these two lines also satisfy part of the reviewers next comment regarding the definition of the (RF) priors.

7. Page 4, lines 29-32. Why the match between prior and posterior distributions in figure 3 changes so much between cases A and B? The authors somehow discuss this in lines 6-12 of page 5, but the change is impressive. Can the authors say something more about this?

We have added a short comment on this in the text at line 30, page 4 in the previous version:

“The prior anthropogenic mean forcing in 2010 increased from 1.5 to 2.3 Wm<sup>-2</sup> from case A to case B when Forc\_AR5 replaced Forc\_Skeie14. For case A, the posterior forcing is shifted upwards compared to the prior, suggesting that the data supports higher values than the Forc\_Skeie14 prior used in this case. When the prior is changed to Forc\_AR5 in case B, the posterior is much closer to the prior which indicates that the data is more in accordance with the new prior than the old one.”

The most uncertain forcing mechanism is the aerosol ERF, and we also discuss the aerosol ERF prior and posterior in more detail and therefore have we added a new figure number 4, with a panel similar to figure 1 but for aerosol ERF in year 2010, a panel with prior and posterior pdf for the aerosol ERF for case B and a panel for a scatter density plot for aerosol ERF and ECS<sub>inf</sub> for case B.

Note also that a clear definition of the priors is somewhat missing in this paper (the one of the equilibrium climate sensitivity for example is not mentioned at all). The authors probably assume that the reader should go looking for it in Skeie & al (2014), which I did, but it is one of those things that should be repeated also in this paper when presenting the methods;

We have added the priors for the ECS in the methods section and included a table in the supplementary material for the informative priors for the other parameters in the SCM.

In the method section we now include: “The unknown quantities are given prior distributions as presented in Skeie et al. (2014). The ECS is given a vague prior, uniform (0,20) and the informative priors for  $\theta$  based on expert judgment are listed in Table S2. “

8. Page 5, lines 25-30. The data from Ishii and Kimoto are completely out of the confidence interval, in particular in case B. Can the authors comment about this?

Reviewer 2 has the same comment. We have added the following sentence to the manuscript:

“Remark that the Ishii and Kimoto series is out of the 90% CI. The reason is that the assumed observational errors for all series are much larger back in time than in the recent years (Appendix A). Therefore the various data series are aligned quite close to each other in the recent years, and since the Ishii and Kimoto series has a much weaker trend than the others, it lies above the 90% CI in the first part of the data history.”

9. Page 6, lines 22-23. “... and hence no reason to refine the IPCC 2013 aerosol ERF best estimate yet.”, there is something wrong with this sentence;

We have replaced the sentence by “These recent studies indicate that there is no reason to refine the IPCC 2013 aerosol ERF best estimate yet.”

10. Page 7, lines 8-14. If the authors had used the same errors as in Johansson & al (2015), how would the range of climate sensitivity differ? In other words, how much of the larger range is due to considering larger errors and how much to the differences between their methods? Can they comment on this here?

This is a nice suggestion for a further study, preferentially in a multimodel study. As we stated in the text it would have been of great value to do a multi-model intercomparison of observational methods using identical input data to investigate the uncertainties due to different models.

Beside this, there are a number of typos and errors that should be taken care of. For example, use CI instead of C.I., consistently with the use of other acronyms. Please revise the paper also from this point of view.

All C.I. are replaced by CI and some other small typos are corrected.

## Anonymous Referee #2

This paper is an updated analysis of Skeie et al., 2014, using the same simple model and analysis method, but updated radiative forcing (following IPCC AR5), deep ocean data, and updated data to 2014. The paper is very well written and carefully executed. Its a very valuable addition to the literature, and sheds light to the effect of various analysis choices and data uncertainties on the overall ECS result. I also like the discussion of the Johannsen result in comparison to the paper here, which does favour substantially higher ECS values. it is very informative to see this discussion and I find this aspect of the paper particularly valuable.

There are some aspects of the paper that I think could still be improved: a) I find the treatment of gaps in observations opaque. I THINK what happens is that the observations are treated as an estimate of global mean temperature i.e. the fully covered simple model is compared to the observations which do contain missing data. This needs to be clarified. It also affects the results of Richardson et al which are as strong as cited only for the case of comparing a fully covered model with gappy data. If accounting for the actual observational coverage by comparing like with like (model limited to same datapoints), the result gets less sensitive which is reasonable. Its not necessary to change the method, but it is necessary to be clear please. If the full model field is compared to the data, it might also be useful to be more explicit about the lack of coverage in rapidly warming high latitudes. For the deep ocean, it seems that the upper 700m are compared in model and data for the upper ocean case only - this could be again said more explicitly

The SCM calculates hemispheric temperatures for blended SST and SAT. For observed surface temperature we use several data series, some with a greater global coverage than others. For instance HadCRUT4 with more gaps, compared to CowtanWay with a larger degree of infilling. However, considering the whole time period, there are also large uncertainties related to these infilling methods. Since our SCM does not have a spatial grid structure, we cannot filter out regions that have very sparse observations. Thus in the model we have chosen to use them all, with the interpretation that they represent the hemispheric temperatures of the SCM. In the introduction we insert a sentence regarding the gappy data to highlight this point: "Several observed surface temperature records exist with different methods to account for spatial gaps in the observations".

In the method section we have include a short description of the SCM, and specify that it calculate hemispheric temperatures for blended SST and SAT, se response to reviewer 1 above.

Replying to your last comment, the text describing the sensitivity test regarding the deep ocean data in the appendix is merged with the existing text in section 4.1. We hope this will make it clearer.

b) prior: while I am not as convinced that the nonanonymous reviewer about the value of an objective prior, I did like that earlier papers of this group showed results using different priors. I think it would be nice to do this here as well in order to illustrate to what extent the prior still matters.

N. Lewis has a related comment, see below. To demonstrate the sensitivity of the prior for ECS, we have computed an alternative estimate of ECS using another prior, namely where  $1/ECS$  is uniformly distributed. This is done by importance sampling of the MCMC samples we already have, as described in Appendix E6 in our previous paper Skeie et al. (2014).

"Implementing an alternative prior for  $ECS_{inf}$  as in Skeie14, where  $1/ECS_{inf}$  is uniformly distributed, the 90% CI shift to lower values (0.97 to 2.5°C). The  $ECS_{inf}$  estimate is sensitive to the prior, however this

alternative prior is strongly informative towards low climate sensitivities that may not be realistic (Aldrin et al. 2012, Skeie et al. 2014).”

c) the plotted updated Skeie 2014 analysis is different from the published version - I would find it cleaner to also add the originally published range in figure 1.

We have added the original Skeie 2014 range to figure 1.

d) it would be nice to see a bit more about the TCR results here as well.

We will add the TCR results as a separate panel in figure 1 as well as a few more additional sentences in the main text presenting the TCR results.

e) The sensitivity tests are interesting and it would be useful to discuss some of them in the body of the text, particularly the case of efficacy - maybe even give some further ranges in abstract. There is clearly some sensitivity here that isn't accounted for in the main result, so this should be made more clear.

We have moved the text regarding the efficacy to the discussion section in the main body of the text.

“Recently, studies have suggested that assuming equal efficacy for all forcings bias the ECS estimate low (Marvel et al., 2015; Shindell et al., 2015) even when ERFs are used. In our approach, the efficacy is implicitly included in the forcing uncertainty and thus accounted for. However, if we apply a efficacy of 1.5 for ozone, surface albedo, BC on snow and aerosols, which is the efficacy found in the analysis of Shindell (2014), the PDF of the ECS is shifted to larger values, with a 90% CI ranging from 1.2 to 3.7°C.”

In the abstract we have now specified that the values and ranges given are from our main analysis, indicating that sensitivity test may give different results.

f) it is not quite clear to me how internal climate variability is treated. I assume it is done as in the main Skeie et al., 2014 result, i.e. assuming that internal variability is reflected in the residual and no additional estimate is given. It would be informative to hear how this estimate compares for example to model estimates. It is interesting to hear that the updated RF series yields smaller residuals.

In the model section we have now included a paragraph explaining the three terms representing variability and model error to make this clearer.

“...where  $\mathbf{n}_t$  is a stochastic process, with three terms, representing long-term and short-term internal variability and model error. For the short-term internal variability, we use the Southern Oscillation index (Table 1) to account for the effect of ENSO. The term for the long-term internal variability were implemented in Skeie14 and the dependence structure of this term (i.e. correlations over time and between the three elements) is based on control simulations with a GCM from CMIP5 (see Skeie14 for details) but the magnitude is estimated from the data. This term will also represent other slowly varying model errors due to potential limitations of the SCM and forcing time series. The third error term is included to account for more rapidly varying model errors.”

We put the estimated amplitudes of the internal variability terms ( $\mathbf{n}_t$ ) in context with the results from unforced control simulations with the ESM models participating in CMIP5 (Palmer and McNeall, ERL, 2014). We will add the following in the result section:

“The estimated amplitude of the multidecadal internal variability (about 0.2°C in each hemisphere, cf. Figure S5) is in good agreement with the decadal trends in global surface temperatures from unforced control simulations in the multimodel ensemble from CMIP5 (0.2-0.4°C, Palmer and McNeall, 2014)”

g) should we treat the main analysis B as the more reliable result or the total OHC using 4 series case C? its is quite remarkable how much the pdf shifts in the latter case. Is the model good enough to reliably separate upper and lower ocean? there is some good discussion in the paper but I am left undecided about this. A bit more clarity would be helpful.

When OHC above and below 700m is merged, most of the heat is stored in the upper 700m (as shown in Fig S7 which we will move to the main text) while the observations show an increase in OHC in the deeper layers. The aerosol forcing is then allowed to be stronger, and  $ECS_{inf}$  is shifted to larger values. The model is simple, and we acknowledge that when this point is discussed in section 5 (page 9 line 1-7 in the original manuscript), however, we believe separating above and below 700m is more realistic and thus case B is our best estimate. Regardless of which estimate is the better, a key finding is that information about the vertical structure of the OHC trends constrains the aerosol forcing and thus provides a potential avenue for improved ECS estimates.

At the end of presenting the results for case C in section 4.2 we add the following sentence: “We therefore keep case B as our main estimate, since having separate data series for the two ocean layers provides information that influence the balance between negative and positive forcings, due to their different time evolution.”

Small comments: p 3 model section: should this refer here already to using the Andronova and Schlesinger model? also, what are the 7 parameters? this would be very useful to hear what they parameterize and which parameter uncertainties are systematically investigated and which are not. this is probably retrievable from earlier papers but worth reiterating here.

We have included a paragraph describing the SCM model at the beginning of the model section and added a table in the supplementary material with the SCM parameters and their prior uncertainty ranges. See our response to similar comments from reviewer 1.

Figure 5 discussion and caption: It would be helpful for a reader to understand what case B,C,D are from the caption - I got it on second but not first reading. (eg averaging rather than separate treatment etc).

The text in appendix D describing the test in case C and D is now merged with the main text. We hope this will make it clearer. In addition, we have added text to the caption. The new caption for figure 5 is now:

“Figure 5: Observed and fitted (posterior mean) total OHC using several OHC dataset (case B: separate OHC data above and below 700m and C: merge OHC data above and below 700m, left panel) and using only one dataset for the total OHC (case D, right panel). The shaded areas indicate the 90% CI.”

In figure 4, I find it slightly confusing that one of the OHC series is systematically outside the estimated 90% range. can this be explained in the text?

See our response to a similar comment from reviewer 1.

### Short comments by N. Lewis

In my view the article, while in principle suitable for publication by ESD, would be much improved if the following issues were addressed:

1. The information provided on the results is too limited. The median is a more appropriate



best estimate measure than the mean for skewed distributions such as that for ECS. That is why the IPCC AR5 report gave medians, but not means, for all the observationally-based ECS estimates that it showed (Figure 10.20b). The medians should be shown, at least for the ECS and TCR posteriors, either instead of or in addition to the means, and likewise given in the Abstract and the main text. It is also slightly strange, for a Bayesian analysis, that the posterior PDF for ECS is only shown in panel j) of Figure S1.

As a response to this point, we have added the medians as triangles in Figure 1. Figure 1 will now also include a panel for TCR, and the medians are included in that figure as well. The median numbers are also included in the abstract and in the main text in addition to the mean values for case A-E.

The posterior PDFs for  $ECS_{int}$  and TCR for case A to E are added to the supplementary material as Figure S2.

2. The TCR estimate is of interest to readers as well as the ECS estimate, but it only seems to feature in Figure S2, with no values given. The Main analysis median TCR estimate and its 5-95% uncertainty range should be stated in the main text and, preferably, also in the Abstract.

As stated above, a panel for the TCR values are now included in Figure 1. We have included the main analysis median and 5-95% range in the main text and added a sentence regarding TCR in the abstract.

3. The study uses a subjective Bayesian analysis. The priors used likely have a major influence on the results, but finding out what they are requires referring to both Skeie et al 2014 and Aldrin et al 2012. A wide uniform prior seems to be used for ECS. It is well known that doing so biases ECS estimation upwards and greatly fattens the upper tail of the posterior. (Annan and Hargreaves 2011: "We show that the popular choice of a uniform prior has unacceptable properties and cannot be reasonably considered to generate meaningful and usable results."; Lewis 2014). Using a noninformative joint prior would produce estimates that were at least approximately unbiased, but calculating one could be difficult. Providing results based purely on the joint likelihood function, using a frequentist profile likelihood method, would be a reasonable alternative. If, as seems likely to be the case, the profile likelihood peaks at approximately the same point as the marginal likelihood for ECS (being the mode of the posterior, as a uniform prior for ECS is used) then the maximum likelihood estimate for ECS would be  $\sim 1.75$  K.

Also, showing what the characteristics of the ECS posterior are when a prior for ECS that is uniform in  $1/ECS$  (and therefore is proportional to  $1/ECS^2$ ) is used would be helpful. That prior will be close to noninformative. [Given that fractional uncertainty in forcing (RF) is approximately symmetrical (Fig. 3(b)) and dominates that in GMST (and in ocean heat uptake), a uniform prior will be approximately noninformative for  $1/ECS$ , and on a change of variable to ECS a uniform prior becomes  $1/ECS^2$ .]

To demonstrate the sensitivity of the prior for ECS, we have computed an alternative estimate of ECS where the prior for  $1/ECS$  is uniformly distributed, see our answer to a comment from reviewer 2.

4. The stepwise update results are interesting, but difficult to interpret in the absence of adequate quantitative information as to the changes in data values and uncertainty ranges involved.

We have now merged the text in the appendix B and the text on page 5-6 for the stepwise update to make this clearer, and we have added the 90% CI for each step in the text.

# Climate sensitivity estimates – sensitivity to radiative forcing time series and observational data

Ragnhild Bieltvedt Skeie<sup>1</sup>, Terje Berntsen<sup>1,2</sup>, Magne Aldrin<sup>3</sup>, Marit Holden<sup>3</sup>, and Gunnar Myhre<sup>1</sup>

<sup>1</sup>CICERO-Center for International Climate and Environmental Research – Oslo, PB. 1129 Blindern, 0318 Oslo, Norway.

<sup>2</sup>Department of Geosciences, University of Oslo, PB. 1047 Blindern, 0316 OSLO, Norway.

<sup>3</sup>Norwegian Computing Center, PB. 114 Blindern, 0314 Oslo, Norway

*Correspondence to:* Ragnhild Bieltvedt Skeie ([r.b.skeie@cicero.oslo.no](mailto:r.b.skeie@cicero.oslo.no))

**Abstract.** Inferred Effective Climate Sensitivity ( $ECS_{inf}$ ) is estimated using a method combining radiative forcing (RF) time series and several series of observed ocean heat content (OHC) and near-surface temperature change in a Bayesian framework using a simple energy balance model and a stochastic model. The model is updated compared to our previous analysis by using recent forcing estimates from IPCC, including OHC data for the deep ocean, and extending the time series to 2014. ~~The~~In our main analysis, the mean value of the estimated  $ECS_{inf}$  is 2.0°C, with a median value of 1.9°C and a 90% credible interval (CI) of 1.2-3.1°C. The mean estimate has recently been shown to be consistent with the higher values for the equilibrium climate sensitivity estimated by climate models. The transient climate response (TCR) is estimated to have a mean value of 1.4°C (90% CI 0.9 - 2.0°C), and in our main analysis the posterior aerosol effective radiative forcing is similar to the range provided by the IPCC. We show a strong sensitivity of the estimated  $ECS_{inf}$  to the choice of a-priori RF time series, excluding pre-1950 data and the treatment of OHC data. Sensitivity analysis performed by merging the upper (0-700m) and the deep ocean OHC or using only one OHC data set (instead of four in the main analysis), both give an enhancement of the mean  $ECS_{inf}$  by about 50% from our best estimate.

## 1 Introduction

A key question in climate science is how the global mean surface temperature (GMST) responds to changes in greenhouse gases or other forcings. The climate sensitivity is determined by complex feedbacks that operate on very different timescales and may depend on the transient climate state. The standard metric for climate sensitivity is the equilibrium climate sensitivity (ECS) (or Charney sensitivity) given as the change in temperature at equilibrium for a doubling of  $CO_2$ , neglecting long-term feedbacks associated with the vegetation changes, carbon feedbacks and ice sheet dynamics. Estimates of the ECS are either based on complex climate models or observations of past climate (Collins et al., 2013; Knutti et al., 2017). The

Intergovernmental Panel on Climate Change (IPCC) presented a likely (>66% probability) range for ECS of 1.5 to 4.5°C (Collins et al., 2013).

Regarding the Earth as a climate laboratory and the changes in atmospheric composition and land use over the historical record as a perturbation experiment, observational based analysis of Earth's Energy Budget have been used to infer the climate sensitivity (Forster, 2016). Since the current climate is in a non-equilibrium state, observationally based methods can only account for the feedbacks operating during the historical period. ~~Thus, these estimates~~ These methods using the historical period with observations are ~~often~~ referred to as inferred ~~or effective climate sensitivity estimates~~ (Armour, 2017;Forster, 2016) and have only the capability to derive an effective climate sensitivity and are generally significantly lower than ECS estimates from Atmosphere-Ocean General Circulation Models (AOGCMs). ~~(Armour, 2017;Knutti et al., 2017).~~

Since IPCC's fifth assessment report (AR5) there has been an improved understanding of the causes of the differences in estimates of climate sensitivity from climate models and observational based methods, directed to two main reasons. First, recent analysis of time-varying feedbacks in AOGCMs simulations from Coupled Model Intercomparison Project Phase 5 (CMIP5) (Proistosescu and Huybers, 2017;Armour, 2017;Andrews et al., 2015) have indicated that in most AOGCMs the net feedbacks become more positive over time as a new equilibrium is approached. This is most likely due to evolution of the pattern of sea surface temperature increase in the Pacific and Southern Ocean and associated cloud feedbacks. Whether this slow warming has manifested itself in the climate record used for the analysis is the difference between effective and equilibrium climate sensitivity (Armour, 2017;Knutti et al., 2017). Second, ECS formally refers to global near-surface air temperature ('tas' in CMIP5 nomenclature) and in observational based methods observed surface temperature records ~~which are a blend of air temperature over land and sea surface temperature over ocean are used in the estimation~~ that are a blend of air temperature over land and sea surface temperature (SST) over ocean are used in the estimation. Several observed surface temperature records exist with different methods to account for gap in the observations. Differences in historical surface temperature warming among various analysis is more than 0.1°C (Haustein et al., 2017) arising mainly due to approaches taken in regions missing or limited spatial coverage of observations. According to Richardson et al. (2016), there is a general bias in the surface temperature records since water heats slower than the air above and due to undersampling in fast warming regions (e.g. the Arctic). Taking both effects into account, Armour (2017) shows that previous estimates of ECS<sub>mf</sub> of about 2.0°C are consistent with estimates of ECS of 2.9°C from climate models.

Although it is now established that the ECS estimated by the use of complex climate models and ECS<sub>mf</sub> estimated by using historical observations would differ, there is still considerable spread in ECS estimates from models and between observationally based ECS<sub>mf</sub> estimates. The observational based methods and using complex models are complementary approaches to quantify the net effect of the feedbacks that determines the climate sensitivity. Complex climate models include processes that are highly parameterized, in particular the representation of clouds, precipitation and convection, and associated feedbacks, which are crucial for estimating the ECS (Bony et al., 2015;Tan et al., 2016). There are also a large spread in observational based estimates (Knutti et al., 2017). Better understanding of the feedbacks in the complex models as well as improvements and understanding differences among the observational based methods are needed.

Observational estimates of climate sensitivity can be improved using longer data series of higher quality (e.g. correcting for observational biases in temperatures or better forcing estimates) (Urban et al., 2014). Estimates can also be improved by including observational data on other climate variables, which were not previously available. Several studies indicate that the temporary slowdown in GMST in the beginning of the millennium coexisted with increased accumulation of heat in the deep ocean (e.g. Meehl et al., 2011; Meehl et al., 2013; Balmaseda et al., 2013; Watanabe et al., 2013; Chen and Tung, 2014; Lyman and Johnson, 2013). Johansson et al. (2015) found that if OHC change below ~~700-meter~~700m over this period were included in their observational based methods the mean value of  $ECS_{inf}$  increased.

In this study we use our estimation model (~~ref. sect. 2, Aldrin et al., 2012; Skeie et al., 2014~~) ~~with additional and extended observational datasets (including heating rates of the deep ocean) and new forcing time series to update our estimate of  $ECS_{inf}$  that were first documented in Aldrin et al. (2012) and further developed in Skeie et al. 2014.~~ Our method is more complex than the common energy balance based estimates (Forster, 2016) in that we embed a simple climate model into a stochastic model with radiative forcing time series as input, treating the northern and southern hemisphere (NH and SH) separately and includes a vertical resolution of the ocean (40 layers). ~~The Markov Chain Monte Carlo~~The radiative forcing time series are linked to the observations of OHC and temperature change through the simple climate model and the stochastic model, using a Bayesian approach. A unique feature with our method used is that we use several observational datasets. The method estimates not only the  $ECS_{inf}$  but simultaneously also provides posterior estimates of the radiative forcing, as well as posterior uncertainty estimates in the observations datasets and correlations between them. In this study we further develop our estimation model with additional observational datasets, including heating rates of the deep ocean (below 700m), new forcing time series from the IPCC AR5 as well as extended time series from 2010 to 2014 to update our estimate of  $ECS_{inf}$ .

We carry out a number of sensitivity experiments to investigate causes of differences in observational based  $ECS_{inf}$  estimates due to differences in the input data (observations of surface temperature, OHC and RF).

## 2 Data and methods

### 2.1 The model

Our full model consists of a simple climate model (SCM) with an idealized representation of the Earth's energy balance, a data model that describes how observations are related to the process states, and finally a parameter model that expresses our prior knowledge of the parameters (Aldrin et al., 2012).

The core of our model framework is the SCM, a deterministic energy balance/upwelling-diffusion model (Schlesinger et al., 1992). The SCM calculates annual hemispheric near-surface temperature change (blended SST and surface air temperature) and changes in global OHC as a function of estimated RF time series. The vertical resolution of the ocean is 40 layers down to 4000m. The output of the SCM can be written as  $m_t(x_{1750:t}, \theta)$ , where  $x_{1750:t}$  (the RF from 1750 until year t) and  $\theta$  are the true, but unknown, input values to the SCM.  $\theta$  is a vector of seven parameters, each with a physical meaning. One of these parameters is the climate sensitivity, and the other parameters determine how the heat is mixed into the ocean, which includes

the mixed layer depth, the air-sea heat exchange coefficient, the vertical diffusivity in the ocean and the upwelling velocity (see Schlesinger et al. (1992) and Aldrin et al. (2012) for details). ~~The true state of some central characteristics ( $g_t$ ) of the climate system in year t with corresponding observations can be written as  $g_t = m_t(x_{1750:t}, \theta) + n_t$ . Here,  $m_t$  is the output from the deterministic SCM, whereas~~

5 ~~The true state of some central characteristics ( $g_t$ ) of the climate system in year t with corresponding observations can then be written as  $g_t = m_t(x_{1750:t}, \theta) + n_t$ , where  $n_t$  is a stochastic process, with three terms, representing long-term and short-term internal variability and model error. For the short-term internal variability, we use the Southern Oscillation index (Table 1) to account for the effect of ENSO. The term for the long-term internal variability were implemented in Skeie et al. (2014) and the dependence structure of this term (i.e. correlations over time and between the three elements) is based on control simulations with a GCM from CMIP5 (see Skeie et al., 2014 for details) This term will also represent other slowly varying model errors due to potential limitations of the SCM and forcing time series. The third error term is included to account for more rapidly varying model errors.~~

10 ~~For the (available) long-term observational data that defines  $x_{1750:t}$  (the RF from 1750 until year t) and  $\theta$  are the true, but unknown, input values to the SCM.  $\theta$  is a vector of seven parameters, each with a physical meaning. One of these parameters is the climate sensitivity. Finally,  $n_t$  is a stochastic process, with three terms, representing long term and short term internal variability and model error (Skeie et al., 2014).~~

15 ~~For  $g_t$  we consider the surface temperatures separately atfor the northern and southern hemispheres and the OHC separately for 0-700m and below 700m. Each of these elements of  $g_t$  are associated with one or more corresponding observational-based data series (Table 1), with individual error terms (Table 1). To gain as much information as possible, we use several data sets for the same physical quantity (e.g. OHC above 700m) simultaneously (Aldrin et al., 2012; Skeie et al., 2014). Most of the data series are provided with corresponding yearly standard errors. However, these are often small compared to the differences between the data series, indicating that the errors reported by the data providers are too small. Therefore (Fig. S7a). However, we only use the temporal profiles of the reported errors and estimate their magnitudes within the model, taking into account the possibilities that the reported standard errors may under- or overestimate the true uncertainty (Appendix A and Aldrin et al., 2012; Skeie et al., 2014).~~

20 ~~The unknown quantities are given prior distributions as presented in Skeie et al. (2014). We apply a Bayesian approach. The ECS is given a vague prior, uniform (0,20) and the informative priors for  $\theta$  based on expert judgment are listed in Table S1. We apply a Bayesian approach in the spirit of Kennedy and O'Hagan (2001) on calibration of computer models and use Markov Chain Monte Carlo (MCMC) techniques to sample from the posterior distribution. (Aldrin et al., 2012).~~

## 30 **2.12 Set up**

The starting point, here called case A, is the main results from Skeie et al. (2014) (hereafter named Skeie14) with some modifications (see Appendix A). These modifications changed the mean ECS<sub>inf</sub> value from 1.84 to 1.958°C and the (median 1.7°C, 90% credible interval (C.I.) from (CI) 0.92, 3.18) 2°C to (1.04, 3.41) 2.0°C (median 1.8°C, 90% CI 1.0-3.4°C) (Fig.

1a, case A). The transient climate response (TCR) is calculated by running the model with 1% per year increase in CO<sub>2</sub> using the joint posterior distribution of the model parameters, see Fig. S2. These modifications increased the mean value of TCR from 1.4 to 1.5°C and the 90% CI shifted slightly to larger values (Fig. 1b).

In case A, we used four hemispheric pairs of observational based estimates of surface temperatures from about 1880 to 2010 and three series for OHC above 700m from about 1950 to 2010, and RF from Skeie et al. (2011,2014) (Table 1). We now The forcing time series used in case A are hereafter named Forc\_Skeie2014 and the priors of each forcing mechanisms included (Table S2) are described in detail in the appendix D of Skeie14.

The potential for improving the constraint of the estimate of the climate sensitivity using observationally based methods, depends crucially on the quality of the input forcing data and the quality and amount of observational data. In case B, we include new and improved knowledge of the forcing time series and add new data for OHC below 700 meter (ORAS4), as well as ORAS4 OHC data above 700 meter, 700m and observational data are extended to 2014. (More specific in case B) (see Appendix B). We 1) replaced the Forc\_Skeie14 prior with the AR5 effective radiative forcing (ERF) estimates (Myhre et al., 2013) hereafter named Forc\_AR5. The priors for the forcing mechanisms included (Table S2) are constructed to be consistent with the uncertainties provided in AR5 and the same relative uncertainty for the prior forcing is used over the entire time period. ERF includes rapid adjustments allowing the full influence on clouds except through surface temperature changes (Sherwood et al., 2014; Boucher et al., 2013; Myhre et al., 2013). 2) Include data for OHC below 700m (ORAS4) and add one extra data series for OHC above 700m (also ORAS4). Note that the deep ocean OHC is added as a separate dataset and not merged with the upper ocean. The vector  $\theta$  contains several parameters that determine how heat is mixed into the ocean (the rate and vertical structure). This includes the mixed layer depth, the air sea heat exchange coefficient, the vertical diffusivity in the ocean and the upwelling velocity (see Schlesinger et al. (1992) and Aldrin et al. (2012) for details). Including data on OHC in the deep ocean thus has the potential to better constrain  $\theta$ , the parameters in the SCM that determine how the heat is mixed into the ocean as well as the posterior estimates of the effective radiative forcing. 3) Use updated versions of the data prior to 2010, and 4) extend the time series from 2010 to 2014.

Previous studies using similar methods have obtained different results with respect to the estimated ECS<sub>inf</sub> (Knutti et al., 2017).

We perform three sensitivity experiments to investigate the effects of the different choices about how to use of OHC data (cases C and D, sect. 4.1) and how sensitive the results are to pre-1950 data (case E, sect. 4.2).

### 3 Improved estimate of inferred equilibrium effective climate sensitivity

Here we presents present our revised estimate of ECS<sub>inf</sub> by replacing the RF prior with IPCC data, including OHC data below 700 meter and extending the time series to 2014. We replaced the Forc\_Skeie14 with the AR5 effective radiative forcing (ERF) estimates (Myhre et al., 2013), including the AR5 uncertainties. ERF includes rapid adjustments allowing the full influence on clouds except through surface temperature changes.

~~We consider the 700m and extending the time series to 2014 (Case B). We consider this~~ analysis using the IPCC forcing estimates, including deep ocean OHC and extending the length of the input data series as the most trustworthy and physical based case and thus regard it as our main estimate of the  $ECS_{inf}$ , with a mean of  $2.0^{\circ}C$ , ~~and a 90% C.I. of  $1.2-3.1^{\circ}C$ . The mean value is similar while the 90% C.I. is narrower compared to the refined Skeie et al. (2014) estimate (Fig. 1). The mean value of TCR is  $1.4^{\circ}C$  with 90% C.I. of  $0.9-2.0^{\circ}C$  (Fig. S2 (median  $1.9^{\circ}C$ , 90% CI  $1.2-3.1^{\circ}C$ ). The mean value is similar while the 90% CI is narrower compared to the refined Skeie14 estimate (Fig. 1a). The individual influence of the four major updates between case A and B is shown in Fig. S1 and described at the end of this section. The mean value of TCR in case B is  $1.4^{\circ}C$  (median  $1.3^{\circ}C$ , 90% CI  $0.9-2.0^{\circ}C$ ) (Fig. 1b). As for the  $ECS_{inf}$  estimate, the TCR mean value is similar and the 90% CI is narrower compared to the refined Skeie14 estimate (Fig. 1b). The GMST change is well reproduced (Fig. 2, case B), and less of the recent GMST change is attributed to long term internal variability (Fig. S5a-b) compared to the refined Skeie et al. (2014) estimate compared to the refined Skeie14 estimate (Fig. S5a-b).~~

The rate of change in anthropogenic forcing is larger between 1940 and 1970 using Forc\_AR5 compared to Forc\_Skeie14 (Fig. 3). The fit to the GMST in the 1980s-1990s improved (Fig. 2 case B vs. A). ~~The root mean square error between 1980 and 1999 decreased from 0.123 to 0.077. Parts of the increase in GMST over the last decades is explained as long term internal variability, but the amplitude decreases in case B compared to case A (Fig. S5a-b). A), where the root mean square error between 1980 and 1999 decreased from 0.12 to  $0.077^{\circ}C$ . Figure S5 shows posterior estimates of the long-term internal variability, the ENSO term and the model errors. Parts of the increase in GMST over the last decades are explained as long-term internal variability, but the amplitude decreases in case B compared to case A (Fig. S5a-b). In case B, the estimated amplitude of the multi-decadal internal variability (about  $0.2^{\circ}C$  in each hemisphere, cf. Figure S5) is in good agreement with the decadal trends in global surface temperatures found in unforced control simulations in the multi-model ensemble from CMIP5 ( $0.2-0.4^{\circ}C$ , Palmer and McNeall, 2014).~~

The prior anthropogenic mean forcing in 2010 increased from  $1.5$  to  $2.3 Wm^{-2}$  from case A to case B when Forc\_AR5 replaced Forc\_Skeie14. ~~The For case A, the posterior forcing is shifted to higher values compared to the prior, suggesting that the historical data and our method supports higher forcing than the Forc\_Skeie14 prior. When the prior is changed to Forc\_AR5 in case B, the posterior for the anthropogenic forcing is much closer to the prior in case B compared to case A (Fig. 3), even though the prior which indicates that the method and observational data is more in case B is less constrained around the mean value compared to case A accordance with the new prior than the old one.~~ The same holds for the total forcing (Fig. S4). The 90% ~~C.I.CI~~ for the posterior anthropogenic forcing was  $1.3$  to  $2.8 Wm^{-2}$  in case A compared to  $1.3$  to  $3.4 Wm^{-2}$  in case B. The upper limit of the 90% ~~C.I.CI~~ is shifted to larger values. ~~Using Forc\_AR5 allows for stronger positive forcing than using Forc\_Skeie14.~~ The most uncertain part of the forcing time series of ERF is associated with aerosols. The ~~posterior estimated net ERF for aerosols changed difference~~ between case A and B (from  $-1.0 Wm^{-2}$  and  $-0.9 Wm^{-2}$  respectively), while the total ERF ~~two forcing priors is mainly due to a much weaker aerosol forcing in 2010 is  $-0.2 Wm^{-2}$  higher Forc\_AR5 than in Forc\_Skeie14 (compare the two dashed-dotted error bars in Fig. 4a). While the posterior aerosol forcing where shifted to smaller negative values in case A, the prior and posterior for aerosol forcing is similar in case B (Fig. 4b). A relative weak~~



aerosol-cloud interaction as included in Forc\_AR5 is consistent with the recent findings in Malavelle et al. (2017) on how sulphate aerosols from volcanic emissions influences clouds.

The ERFs in AR5 are based on an assessment of several studies reflecting improved knowledge of the forcing mechanisms compared to the one-model RF results used in Skeie14. The new ERFs gave a better posterior estimate of GMST (Fig. 2) and reduced change from prior to posterior forcing (Fig. 3). Remark that the number of forcing time series that can be combined was 18 in Skeie14, including three ~~time series~~ ~~timeseries~~ for volcanic and eight for ~~aerosol~~ ~~aerosols~~, compared to only one time series for each of these forcing mechanisms in Forc\_AR5 (Table ~~S1~~ ~~S2~~). This gives less flexibility in the time development of the forcing in case B compared to case A, however the GMST change is better reproduced in the 1980s-1990s using Forc\_AR5 compared to Forc\_Skeie14.

10 Ultimately, global climate change is governed by the radiative imbalance at the top of the atmosphere (TOA) and modulated by the internal variability. Forcing by greenhouse gases and aerosols as well as albedo changes, feedback processes and the radiative responses to temperature changes determine this imbalance. With a positive net imbalance at TOA, energy accumulates in the Earth system, mainly as increasing OHC (Church et al., 2011). Since OHC is the dominant energy storage in the system, these data series have profound influence on the  $ECS_{inf}$  estimates (Tomassini et al., 2007; Skeie et al., 2014; Aldrin et al., 2012; Johansson et al., 2015). ~~We~~ ~~In case B, we~~ have extended our use of OHC data, so in addition to the three OHC data series above 700m we ~~now include~~ ~~have included~~ the ORAS4 data above and below 700m (Table 1) as two separate data sources. ~~The~~ ~~Including the~~ deep ocean OHC data gives a stronger constraint on the overall accumulation of heat in the system, and the posterior estimates of the parameters of  $\theta$  that determine the vertical transport of heat in the ocean, the effective diffusivity and the upwelling velocity increase by 44 and 31%~~%~~, respectively. Having separate data series for the two ocean layers also provides information that ~~influence~~ ~~influences~~ the balance between negative (by aerosols) and positive forcings, since these forcings have different evolution over time (cf. sect. 4.1).

In Fig. ~~45~~ the observed and fitted OHC for case A and B are shown. Including data on OHC change below ~~700-m~~ ~~700m~~ increases the total heat uptake. The increase in ~~the fitted~~ OHC above ~~700-m~~ ~~700m~~ over the last decade is larger in case B compared to case A. In case B the increase in ~~the fitted~~ OHC above ~~700-m~~ ~~700m~~ is larger than the observational data, while below ~~700-meter~~ ~~700m~~, the observed OHC increase is ~~underestimated~~ ~~higher than the fitted one~~ (Fig. ~~45~~). This is to be expected since the parameters of  $\theta$  do not change over time. Thus, the observed rapid change in OHC below ~~700-meter~~ ~~700m~~ over the last years with corresponding slower warming above ~~700-meter~~ ~~700m~~, is attributed to long-term internal variability (a part of the  $n_t$  term) in the model (Figure S5c-d). ~~Remark that the Ishii and Kimito series is out of the 90% CI. The reason is that the assumed observational errors for all series are much larger back in time than in the recent years (see Appendix A). Therefore, the various data series are aligned quite close to each other in the recent years, and since the Ishii and Kimoto series has a much weaker trend than the others, it lies above the 90% CI in the first part of the data history.~~

The update of the  $ECS_{inf}$  from case A to B (~~changing the forcing prior and including OHC data below 700 meters as well as updated and extended data up to and including 2014~~) ~~were~~ ~~was~~ done stepwise (~~see Appendix B~~). The  $ECS_{inf}$  estimate was very sensitive to the forcing time series used, ~~in four steps (Fig. S1f, g, i and j)~~. The new ERFs were first implemented. ~~That~~ ~~The~~



posterior forcing is much closer to the prior using Forc\_AR5 instead of Forc\_Skeie14, and also the fit to the GMST in the 1980s-1990s improved with a decrease in the root mean square error between 1980 and 1999 from 0.12 to 0.087°C compared to case A. The stronger forcing resulted in a shift of the ECS<sub>inf</sub> estimate to lower values (Fig. S1f vs. e), with an ECS<sub>inf</sub> mean value of 1.5°C and a 5°C (90% C.I. ranging from 0.9 to 2.3°C. Including also the). So far, only OHC data in the upper 5 700m were used, leaving the model unconstrained with respect to the heating of the deeper ocean. We then included the ORAS4 data above and below 700m as two separate data sources. Similar to Johansson et al. (2015) we found that including the OHC change below 700m ~~increased~~ increases the total heat uptake and thus the mean value of ECS<sub>inf</sub> from 1.5 to 1.7°C (Fig. S1g vs. f, see Fig. S1f-g). The 90% CI shifted to larger values ranging from 1.0-2.8°C. The last ~~step~~ two steps to update the ECS<sub>inf</sub> estimate from case A to case B was to ~~extend the data series used. Using~~ 10 ~~observational data up to 2014 as well as use~~ the most recent version of the data prior to 2010 and to extend the data series used from 2010 to 2014 (Table 1). Some of the observational data series have been updated by the data suppliers, so first we use refined data up to 2010 before we extend the data series to 2014 (cf. Appendix B). Using the refined data up to 2010, the estimated mean ECS<sub>inf</sub> increased from 1.7 to 2.0°C (Fig. S1i) and the 90% CI was shifted again to larger values ranging from 1.1-3.3°C. Further, when the data series were extended from 2010 to 2014 the upper bound of the 90% CI decreased from 3.3 15 to 3.1°C while the lower bound remained unchanged and the mean estimate slightly reduced (Fig. S1j.) ~~increased~~ In total, the changing from case A to Case B did not change the mean value of ECS<sub>inf</sub> ~~to~~ (it is 2.0°C and the in both cases), but the 90% CI was reduced from 1.0-3.4 °C to 1.2-3.1°C. The reduction in ECS<sub>inf</sub> in the first step of the update is more or less counteracted ~~by the subsequent steps.~~

#### 4 Sensitivity tests – the use of input data

20 We now investigate possible causes of differences in observational based ECS<sub>inf</sub> estimates due to the use of input data. We analyze the impacts of different usage of the OHC data (cases C and D) and the treatment of uncertainties in the GMST data (case E).

##### 4.1 The role of the use of OHC data

The vertical transport of heat in the SCM (with 40 vertical layers) is quite simple. Turbulent diffusion mixes heat down from 25 the surface, while ~~down welling~~ downwelling transports heat directly to the deepest layer, i.e. no detrainment to intermediate layers (Aldrin et al., 2012). Therefore, ~~one may argue that it might be more appropriate is of interest to only investigate whether~~ a constrain of the model with OHC data for the total depth of the ocean ~~instead of above and below 700 m. In Case C we do not separate the 0-700m from the deeper ocean. We use four data sets for total OHC by adding the ORAS4 below 700m data to each of the four OHC above 700m estimates.~~ Merging the OHC above and below 700m (Case C, ~~see Appendix D~~) results 30 in a substantial decrease in the posterior ERF from 2.5 to 1.8 Wm<sup>-2</sup> (Fig. S7bS6b-c) and an increase in the ECS<sub>inf</sub> estimate from a mean value of 2.0°C ~~in case B (median 1.9°C)~~ to 3.2°C (median 2.9°C) (Fig. 41a). Without the separate constraint on

the OHC above and below 700m, the posterior warming of the ocean increases faster (compared to case B) over the last 20 years (Fig. 56). This is mainly caused by enhanced warming in the upper 700m (Fig. S67). This allows for a stronger negative ERF estimate for aerosols- (Fig. 4a). While the prior and posterior radiative forcing in Case B is similar, in case C the posterior aerosol ERF is shifted to lower values (Fig. 4a), the posterior net forcing in case C is shifted towards lower values (Fig. S7e4a and Fig. S6c) and hence a higher estimated ECS<sub>inf</sub> (Fig. 1) compared to case B. This anti-correlation between aerosol forcing and ECS<sub>inf</sub> is illustrated in Fig. 4c for case B. However, the observations show a stronger recent increase in heat in the deep ocean (c.f. sect. 3), and not in the upper 700m, so this test might where this information is not used is likely to overestimate the aerosol forcing strength and hence overestimate the ECS<sub>inf</sub>. Since the IPCC best estimate of  $-0.9 \text{ Wm}^{-2}$  was published in 2013 for aerosols ERF, studies point in different directions of either enhanced or weakened aerosol ERFs towards weak aerosol-cloud interaction (Gordon et al., 2016; Malavelle et al., 2017; Toll et al., 2017), and hence no reason to refine the IPCC 2013 aerosol ERF best estimate yet. These recent studies indicate that there is no firm evidence to revise the IPCC AR5 aerosol ERF best estimate yet. We therefore keep case B as our best estimate, since having separate data series for the two ocean layers provides information that constrain the balance between negative and positive forcings, due to their different time evolution.

15 A unique feature with our method is that we use data from more than one observational dataset. It is obvious that, as long as the various data series for the same quantity (here OHC above 700m) differ, it is easier to fit a model to one data series, thus giving less uncertainty in the posterior estimates. In case D we test the effect of using one alternative time series for OHC-We choose to use the Levitus2000 time series, that is the same OHC data as used in Johansson et al. (2015). The pentadal heat content are used from 1955 to 2012, treated as annual observations, and extended to 2014 using the yearly OHC data for the

20 upper 2000m from the same data source. We use the OHC data for the upper 2000m as they were data for the total OHC. Observed energy stored below 2000m is not included in the estimation and hence the ECS might be underestimated. Energy stored below 2000m is uncertain. Purkey and Johnson (2010) found an increase in OHC in the abyssal and deep Southern Ocean in the 1990s and 2000s based on sparse observations from ships, but it is not clear if it is a long-term trend. Llovel et al. (2014) could not detect deep-ocean (below 2000 meter) contribution to sea level rise and energy budget between 2005 and

25 2013 using ocean observations and satellite measurements, however the uncertainties are large. data, see Appendix D). As in case C, we do not separate the OHC data above and below 700m. Quite similar to case C, there is a more rapid increase in the posterior estimate of total OHC (Fig. 56) compared to case B, the increased warming is mostly in the upper 700-meter700m (Fig. S67) and the posterior forcing is shifted to lower values than in the prior (Fig. S7d4a and Fig. S6d). In case D the estimated mean ECS<sub>inf</sub> is  $2.8^{\circ}\text{C}$  with a (median  $2.6^{\circ}\text{C}$ , 90% C.I. of CI  $1.5$  to  $4.6^{\circ}\text{C}$  ) (Fig 1a, case F).

30 This is higher than in case B, but lower than for case C.

The estimated total OHC has a narrower range when OHC above and below 700-meter700m are merged (Fig. 56, left panel). The range is also narrower in case D than in case C. As expected, using several data series for OHC (Case B: 5, Case C: 4, Case D: 1) increase the posterior observational error. Note that the magnitude of the observational errors are estimated (Aldrin et al., 2012; Skeie et al., 2014). In case D, the posterior standard deviation of the observed OHC is similar to the reported

standard deviation, (Fig. S8), while using several OHC time series the posterior standard deviation is larger (Fig. S7) and arguably more correct than reported due to the large variability among the datasets. (Appendix A). Hence, larger uncertainties in the observed OHC data result in larger uncertainties in the estimated OHC.

5 Johansson et al. (2015) used the same OHC data series as in our case D and a similar method, however their 90% ~~CI~~ for the OHC in the upper ~~2000 meter~~2000m (their Fig. S5) is even narrower. This might not only be due to the use of one OHC dataset. While we estimate the magnitude of the observational error, Johansson et al. (2015) use the error given by the OHC data provider. In Johansson et al. (2015) the estimated uncertainties in OHC were smaller than the given observational uncertainties (their Fig. S5). The narrower  $ECS_{inf}$  range may primarily be because Johansson et al. (2015) assumed very small measurement errors in the most informative data (OHC), secondly that they ignored time correlation in observational errors and did not take into account long-term internal variability in the same degree as in our method.

10 To sum up, using several observational series (and estimate observational errors) increase the estimated observational errors to more realistic values, since data series are not well correlated, and hence increase the range of estimated OHC with implications on estimated  $ECS_{inf}$ .

#### 4.2 The role of uncertainty estimates in the temperature series

15 The ~~a-priori~~prior standard deviation for the surface temperature data are quite different among the data sets (Fig. S8S7a). The NCDC data has 3 to 5 times larger standard error prior to 1950 compared to after 1950, while it is more constant back to the 19<sup>th</sup> century for the three other data sets.

To investigate this, we re-estimated our model using data only after 1950, which is equivalent to assuming a very large uncertainty prior to 1950. The estimated magnitude of the ENSO-signal increases (Fig. S5a-b) since the data series are more  
20 correlated in the latter part of 20<sup>th</sup> century. For temperature, the model fits well to the observations of GMST, but with a larger 90% ~~CI~~ range (Fig. 2) and the observed NH and SH temperatures are well within the 90% ~~CI~~ of the model (Fig. S9). The mean  $ECS_{inf}$  increases from 2.0 (median 1.9 °C) to 2.2°C (Fig. 1, case E vs. B) median 2.1°C) and the upper 90% ~~CI~~ limit increases from 3.1 to 3.8°C. (Fig. 1a, case E vs. B). The mean TCR increases from 1.4 to 1.5°C and the 90% CI is shifted slightly to lower values compared to the range from IPCC by 0.1°C (Fig. 1b).

25 Johansson et al. (2015) used only the NCDC data for GMST, thus the data prior to 1950 was given little weight when fitting the model. Our ENSO signal is now (case E) of similar magnitude as in Johansson et al. (2015)- (their Fig. 1b). The  $ECS_{inf}$  uncertainty in this study is still larger and our mean value is slightly higher than their lower limit of 2°C.

Excluding data before 1950 also excludes the late 19<sup>th</sup> century period with a large volcanic eruption where the signal in the GMST data is small and quite uncertain (Santer et al., 2016). Santer et al. (2016) argued that the method in Johansson et al.  
30 (2015) down weights the volcanic forcing due to the small response of the Krakatau eruption in the temperature data. Johansson et al. (2016) responded that the observational uncertainty ~~were~~was large so the GMST data at that time will have a limited effect. In our results, excluding observations before 1950, the GMST response following the Pinatubo eruption in 1991 increases (Fig. 2) and are similar to observations due to the larger ENSO signal and stronger ~~posterior~~posterior volcanic signal.

In the early period, the aerosol forcing had a larger relative contribution to total ERF causing a more uncertain forcing trend in the early period. Uncertainty in the temporal trend of the forcing is not included, and better representation of forcing uncertainties than the scaling approach is needed (Tanaka et al., 2009). Omitting data before 1950 (case E), when the net forcing is more uncertain (Stevens, 2013), makes it easier to fit the model to observations but the uncertainty in estimated

5 ECS<sub>inf</sub>, TCR and GMST and TCR-increases (Fig. 1, and 2-and Fig-S2).

## 5. Discussions and conclusions

Causes of differences in observational based estimates of ECS<sub>inf</sub> due to the use of input data are analyzed and an updated ECS<sub>inf</sub> estimate is presented using our Bayesian estimation model. Adding observational data from 2011 to 2014, OHC data below ~~700-meter~~700m and replacing forcing data with IPCC AR5 ERFs, the ECS<sub>inf</sub> posterior mean was 2.0°C ~~with~~(median 1.9°C,  
10 90-%-C.I.-of-% CI 1.2-to- 3.1°C-). The mean value is similar and the range is slightly narrower than the refined Skeie14 estimated (Fig. 1 case B vs. A). The mean ECS<sub>inf</sub> estimate is larger than in ~~Skeie et al. (2014)~~Skeie14. Although the estimate in case A and B are quite similar, the ECS<sub>inf</sub> estimate shifted to lower values when Forc\_AR5 replaced Forc\_Skeie14 from a mean ECS<sub>inf</sub> estimate of 2.0°C to 1.5°C and shifted to larger values when OHC data below 700m were included to a mean ECS<sub>inf</sub> value of 1.7°C. The ECS<sub>inf</sub> estimate was very sensitive to the forcing data used and we showed that the ECS<sub>inf</sub> estimate  
15 was also sensitive to the assumed uncertainties in the GMST data (Case E, ECS<sub>inf</sub> mean value increased from 2.0 to 2.2°C) and how the OHC data were treated- (Case C and D, with mean ECS<sub>inf</sub> of 3.2 and 2.8°C respectively).

Bayesian methods have recently been reviewed by Annan (2015) and Bodman and Jones (2016) and limitation by assuming constant sensitivity over time, the role of the ECS<sub>inf</sub> prior distribution and equal efficacy for different forcings have been discussed. Implementing an alternative prior for ECS<sub>inf</sub> as in Skeie14, where 1/ECS<sub>inf</sub> is uniformly distributed, shifted the mean  
20 ECS<sub>inf</sub> to lower values from 2.0°C (median 1.9°C, 90% CI 1.2-3.1°C) to 1.6°C (median 1.6°C, 90% CI 0.97-2.5°C). The ECS<sub>inf</sub> estimate is sensitive to the prior, however one could argue against this alternative prior because it has high probability for low climate sensitivities that may not be realistic, with 76% probability for ECS<sub>inf</sub> being lower than the pure black-body radiation sensitivity of 1.1°C (Aldrin et al. 2012, Skeie et al. 2014). Recently, studies have suggested that assuming equal efficacy for all forcings bias the ECS estimate low (Marvel et al., 2015; Shindell et al., 2015) even when ERFs are used ~~(see also Appendix~~  
25 D). In our approach, the efficacy is implicitly included in the forcing uncertainty and thus accounted for. However, if we apply an efficacy of 1.5 for ozone, surface albedo, BC on snow and aerosols, which is the efficacy found in the analysis of Shindell (2014), the probability density function of the ECS is shifted to larger values (Fig. S11), with a 90% CI ranging from 1.2 to 3.7°C.

The fit to the temperature data in the 1980s and 1990s improved using Forc\_AR5 instead of Forc\_Skeie14 indicating that the  
30 forcing trend over this period is better represented in Forc\_AR5 compared to Forc\_Skeie14. The trend in the forcing is more uncertain in the first half of the 20th century due to less dominance of CO<sub>2</sub>, and in our method the same relative uncertainty for the prior forcing is used over the entire time period. A sensitivity simulation omitting observations before 1950, similar to

making these observations very uncertain, gave better representation of the GMST in the latter part of the 20th century and an increased mean ECS<sub>inf</sub>. Future work should include uncertainties in the temporal development of the forcing, and there is a clear need for an international effort to establish forcing time series, using a consistent forcing definition and allowing for uncertainties in emissions, to give a better representation of the temporal uncertainties.

5 Including OHC-data below ~~700-meter~~700m shifted the ECS<sub>inf</sub> to higher values. The estimated ECS<sub>inf</sub> was found to be very sensitive to how the OHC data were used. Including four OHC time series, but merging the data above and below ~~700-meter~~700m (case C), the ECS<sub>inf</sub> mean value increased from 2.0 to 3.2°C. The probability of ECS<sub>inf</sub> above 4.5°C increased to 13%, values that are practically excluded in our main estimate (case B). Previous studies have used total column OHC data and due to the simple representation of the ocean one can argue that this ~~is~~might be more appropriate. However, in case C most of the recent increase in OHC in the model occurred in the uppermost ~~700-meter~~700m allowing a stronger aerosol cooling (Fig. S7e4a) and hence a larger ECS<sub>inf</sub>, while the observations indicate that the ocean ~~is~~was warming mainly below ~~700-meter~~700m. Using only the total column OHC might therefore overestimate the ~~ECS<sub>inf</sub> and the~~ aerosol forcing strength and hence the ECS<sub>inf</sub>. We recognize structural uncertainties in the model, and a multi-model intercomparison of observational methods using identical input data would be of great value to investigate these uncertainties.

10  
15 Using only the Levitus2000 series for OHC for the total ocean column (case D), the ECS<sub>inf</sub> 90% ~~C.I.~~CI was shifted to lower values with a range from 1.5 ~~to~~-4.6°C and the range shrunk compared to case C. The historical measurements of ocean temperatures are sparse (Abraham et al., 2013), with large differences between the datasets. The temporal structure of the reported uncertainties differs, and the full uncertainties are often not assessed. Hence, relying on only one OHC series and its reported uncertainty may underestimate the observational uncertainties and hence overestimate the certainties in the estimated OHC with implications for the ECS<sub>inf</sub> estimate.

Recent studies indicate that the upper-ocean warming is underestimated due to the gap-filling methods (Durack et al., 2014; Li-Jing et al., 2015), in which case also the ECS<sub>inf</sub> will be underestimated. Refining historical OHC estimates, not only the best value, but also the uncertainty is crucial for observational based ECS<sub>inf</sub> estimation.

25 Other priorities ~~is~~are to improve the GMST series, including uncertainties, not only the recent trend (Karl et al., 2015; Cowtan and Way, 2014) but also for earlier time periods. Assuming a very large uncertainty prior to 1950, the GMST fit improved, ECS<sub>inf</sub> mean increased while the estimated uncertainty ranges increased.

30 Our ECS<sub>inf</sub> posterior mean was 2.0°C with 90 % ~~C.I.~~CI of 1.2 to 3.1°C. This is consistent with a mean ECS of 2.9°C (Armour, 2017), which compares reasonably well with climate model estimates (Andrews et al., 2012; Forster et al., 2013). A final remark is that it is not obvious that the true ECS is a more relevant metric for the climate sensitivity than the ECS<sub>inf</sub> in a policy context (i.e. the Paris agreement). The United Nations Framework Convention on Climate Change (UNFCCC) has not adopted a pre-defined definition of GMST and the stronger long-term feedbacks found in analysis of CMIP5 simulations (Proistosescu and Huybers, 2017) operates on a time scale longer than the timescale for reaching 2°C.

## Appendix A: Refinement of Skeie14

A few updates/corrections to Skeie14 (Fig. S1a) had to be made prior to the analyses presented in this study. In the Skeie14 study, the standard error of observed OHC above ~~700 meter~~700m for two out of the three series were constant in time, while for the third dataset the standard error decreased with time. Due to the limited observational data back in history (e.g. Abraham et al., 2013), it is reasonable to assume that the shape of the standard error of observed global OHC increase back in time, as for the CSIRO series. Therefore, we now assume a common observational uncertainty temporal profile for OHC above ~~700 meter~~700m equal to CSIRO for all the OHC time series (Fig. S1b). Note that the magnitude of the observational errors are estimated in our approach (Aldrin et al., 2012; Skeie et al., 2014), i.e. we account for the possibilities that the reported observational errors may be biased upward or downwards compared to the real observational errors.

In fact, the results from Skeie et al. (2014, appendix B) indicated that the reported standard errors for the Levitus and the Ishii and Kimoto OHC series were too low. We have investigated this further by the following simple analysis:

Let  $y_{1t}$  and  $y_{2t}$  be two different estimates of the true OHC in year  $t$ . Then  $y_{1t} = \text{"true OHC"} + e_{1t}$  and  $y_{2t} = \text{"true OHC"} + e_{2t}$ . Here,  $e_{1t}$  and  $e_{2t}$  are error terms, with reported standard deviations  $s_{1t}$  and  $s_{2t}$ , and with true, but unknown standard deviations  $\sigma_{1t}$  and  $\sigma_{2t}$ . The difference of the series is  $y_{1t} - y_{2t} = e_{1t} - e_{2t}$ , so even if we cannot observe the errors, we can observe their difference. If the two data series are based on more or less the same data, as for the OHC series used here, one can expect that  $e_{1t}$  and  $e_{2t}$  are positively correlated. Then  $Var(y_{1t} - y_{2t}) = Var(e_{1t} - e_{2t}) \leq (\sigma_{1t}^2 + \sigma_{2t}^2)$ .

We can estimate the average variance of the differences  $y_{1t} - y_{2t}$  over all time points by  $Var^{obs} = 1/(n - 1) \sum_t (y_{1t} - y_{2t} - m)^2$ , where  $m$  is the average of  $y_{1t} - y_{2t}$  and  $n$  is the number of years. This could be compared to the corresponding reported variance under the assumption of uncorrelated errors, by  $Var^{rep} = 1/n \sum_t (s_{1t}^2 + s_{2t}^2)$ , and if the reported standard deviations are correct, then the variance ratio  $Var^{obs}/Var^{rep}$  should be less than or equal to 1. For differences of the Levitus, Ishii and Kimoto and ORAS4 (above 700m) series, the variance ratios are between 2.13 and 3.74 (Table A1), indicating that the reported observational errors for these series are too low, and the real uncertainty may be larger. This is an additional argument for using the CSIRO standard errors for all OHC series.

Another update of Skeie14 that was needed, was to use monthly volcanic RF data (Fig. S1c) compared to yearly data in Skeie14. In addition to the three global mean surface temperature (GMST) time series used in Skeie14, another time series for GMST has been published recently (Cowtan and Way, 2014). This time series find a stronger increasing trend in temperature over the last decade compared to the HadCRUT4 data, due to their method of accounting for the unsampled regions in the world. This ~~data series~~ data series is now included (Fig. S1d).

Our previous studies showed that the correlation between the observational errors in temperature data was almost uncorrelated with the observational errors in the OHC data. Therefore, to simplify the numerical computations, we from now on assume that ~~that~~ these correlations are exactly zero (Fig. S1e).

The estimated  $ECS_{inf}$  for each step in the refinement of Skeie14 is presented in Fig. S1a-e.



## Appendix B: ~~The stepwise update of ECS<sub>inf</sub>~~

The updated estimate of ECS<sub>inf</sub> were done stepwise. Here these steps and the corresponding ECS<sub>inf</sub> estimates are presented. First, Fore\_Skeie14 was replaced by Fore\_AR5 in the estimation. With Fore\_AR5 the prior anthropogenic mean forcing in 2010 increased from 1.5 to 2.3 Wm<sup>-2</sup>, and the posterior forcing is much closer to the prior. The 90% C.I. for the posterior anthropogenic forcing was 1.3 to 2.8 Wm<sup>-2</sup> using Fore\_Skeie14 compared to 1.3 to 3.3 Wm<sup>-2</sup> using Fore\_AR5. The stronger forcing lead to a lower ECS estimate (Fig. S1f vs. e), reducing the mean ECS<sub>inf</sub> to 1.5 °C (0.9–2.3°C). The fit to the GMST in the 1980s–1990s improved and the root mean square error between 1980 and 1999 decreased from 0.123 to 0.087 compared to case A.

So far, only OHC data in the upper 700 meter were used, leaving the model unconstrained with respect to the heating of the deeper ocean. We now include the ORAS4 data above and below 700m as two separate data sources. Similar to Johansson et al. (2015) we find that including OHC change below 700 m increases the total heat uptake and thus the mean value of ECS<sub>inf</sub> (from 1.5 to 1.7°C, Fig. S1g vs. f).

The last step to update the ECS<sub>inf</sub> estimate is to extend the data series used. Some of the observational data series has been updated, so first we use refined data up to 2010 (Fig. S1i) before we extend the data series to 2014 (cf. Appendix C). Using the refined data up to 2010, the estimated mean ECS<sub>inf</sub> increased from 1.7 to 2.0°C, while extending the data up to 2014 slightly reduced the mean ECS<sub>inf</sub> estimate (Fig. S1j). The upper bound of the 90% C.I. decreased from 3.3 to 3.1°C when the data series were extended from 2010 to 2014 (Fig. S1i and S1j) while the lower bound remained unchanged.

## Appendix C: Extending data up to and including 2014

When extending the analysis from 2010 to 2014, not all the time series used in the estimation is available up to and including year 2014. Below is a description of how the different datasets are extended if not available up to 2014.

AR5 ERF: The end year for the forcing time series presented in AR5 is 2011 and has to be extended to 2014. For long-lived greenhouse gases the time series are extended using recent observations of global mean concentrations and the formulas relating concentrations and forcing used in Skeie et al. (2011). Tropospheric ozone, stratospheric ozone, aerosol ERF, land use change, BC on snow and volcanoes are kept constant 2011–2014. Stratospheric water vapor follow methane RF. Contrails RF is extended using aircraft traffic data (<http://airlines.org/data/annual-results-world-airlines/http://airlines.org/dataset/world-airlines-traffic-and-capacity/>). Solar RF is extended using the Physikalisch-Meteorologisches Observatorium Davos (PMOD) composite (Frohlich and Lean, 2004).

CSIRO: Data up to and including 2012 were downloaded. The time series were extended from 2012 to 2014 using the mean rate of change of the other OHC data. The uncertainty in 2014 and 2013 is set equal to the uncertainty in 2012.

ORAS4: ~~Balmaseda et al. (2013)~~ORAS4: Balmaseda et al. (2013) investigated the time evolution of global OHC at different depths of the ocean from 1958 to 2009 using the European Centre for Medium-Range Weather Forecasts ocean reanalysis system 4 (ORAS4). Five ensemble members of ORAS4 are generated that sample plausible uncertainties in the wind forcing,

observation coverage, and the deep ocean. The ORAS4 system runs automatically in operations, with numerical weather prediction forcing and observations that are not manually quality controlled. The 1x1-degree Ocean potential temperature up to December 2014 are made available through the APDRC ([http://apdrc.soest.hawaii.edu/datadoc/ecmwf\\_oras4.php](http://apdrc.soest.hawaii.edu/datadoc/ecmwf_oras4.php)) for one ensemble member. The trend in OHC for the total depth and upper ~~700 meters~~700m from 2010 to 2014 based on the one ensemble member is used to extend the corresponding OHC data for all the five ensemble members from ~~Balmaseda et al. (2013)~~Balmaseda et al. (2013) up to 2014. The data after 2009 are based on the automatic ORAS4 system, and not quality controlled and the results in this paper using the data after 2009 should be interpreted by caution. The same method is used to extend the ORAS4 data from 2009 to 2010 (Fig. S1g-i). From the five ensemble members the estimate with uncertainty is calculated as the annual average and standard deviation of OHC above and below ~~700 m~~700m. The standard deviations are modified by smoothing the curve (9-year moving average) since the curve was otherwise very static.

#### Appendix D: Sensitivity tests

Here we present in detail two of the sensitivity tests in section 4.

~~Case C: The OHC data used to constrain the model are the same series as in case B, but we do not separate the 0-700 meter from the deeper ocean. We use four data sets for total OHC by adding the ORAS4 700-2000 meter data to each of the four OHC above 700 meter estimates.~~

~~Case D: To test the effect of using one time series for the OHC we do a sensitivity test using only one OHC series and without separate constraint on the OHC above and below 700 meter. We choose to use the Levitus2000 time series, that is the same OHC data as used in Johansson et al. (2015). The pentadal heat content are used from 1955 to 2012. The time series are extended to 2014 using the yearly OHC data for the upper 2000 meter from the same data source. We treat the pentadal observations as they were annual observations, and we use the OHC data for the upper 2000 meter as they were data for the total OHC. Observed energy stored below 2000 meter is not included in the estimation and hence the ECS might be underestimated. Energy stored below 2000 meter is uncertain. Purkey and Johnson (2010) found that in the 1990s and 2000s there was an increase in OHC in the abyssal and deep Southern Ocean based on sparse observations from ships, but it is not clear if it is a long term trend. Llovel et al. (2014) could not detect deep ocean (below 2000 meter) contribution to sea level rise and energy budget between 2005 and 2013 using ocean observations and satellite measurements, however the uncertainties are large.~~

Additional analyses:

Fig. S1h): Use the original ORAS4 standard error for OHC above and below 700 meter.

Fig. S1k): A sensitivity test using the same ENSO index as in Johansson et al. (2015). Similar to a sensitivity test in Johansson et al. (2015), the chosen ENSO index had little effect on the ECS estimate.



Fig S11): Shindell (2014) found that the transient climate sensitivity to historical aerosols and ozone is substantially greater than the transient climate sensitivity to CO<sub>2</sub> based on CMIP5 models. This enhanced sensitivity is primarily caused by more of the forcing being located in Northern Hemisphere where it triggers more rapid land responses and stronger feedbacks. Kummer and Dessler (2014) found that assuming larger efficacy (the amount of warming per unit global average forcing divided by the warming per unit forcing from CO<sub>2</sub>) for aerosol and ozone forcing increased the estimated equilibrium climate sensitivity. They suggested that forcing efficacy can explain the disagreement between estimates of climate sensitivity based on the twentieth century observational record and those based on climate models. If we apply a efficacy of 1.5 for ozone, surface albedo, BC on snow and aerosols, which is the efficacy found in the analysis of Shindell (2014), the PDF of the ECS is shifted to larger values, with a 90% C.I. ranging from 1.2 to 3.7K. This is still lower than the estimate by Kummer and Dessler (2014) of 3K and a 90 % C.I. of 1.9–6.8 when they included efficacy. A recent study (Marvel et al., 2015) found that also when using ERF the TCR and ECR are biased low due to different response of the total forcing compared to CO<sub>2</sub> only. The efficacies presented is from one model only.

15 **Data availability.** Several publicly available data sets were used in this study. The specific references to the data sources are given in [tableTable 1](#). Model outputs are available upon request.

**Author contributions.** All authors designed the study and discussed the results; RBS and MH prepared the data; MH performed the simulations; RBS and MH made the figures; RBS prepared the paper with contributions from all co-authors.

**Competing interests.** The authors declare that they have no conflict of interest.

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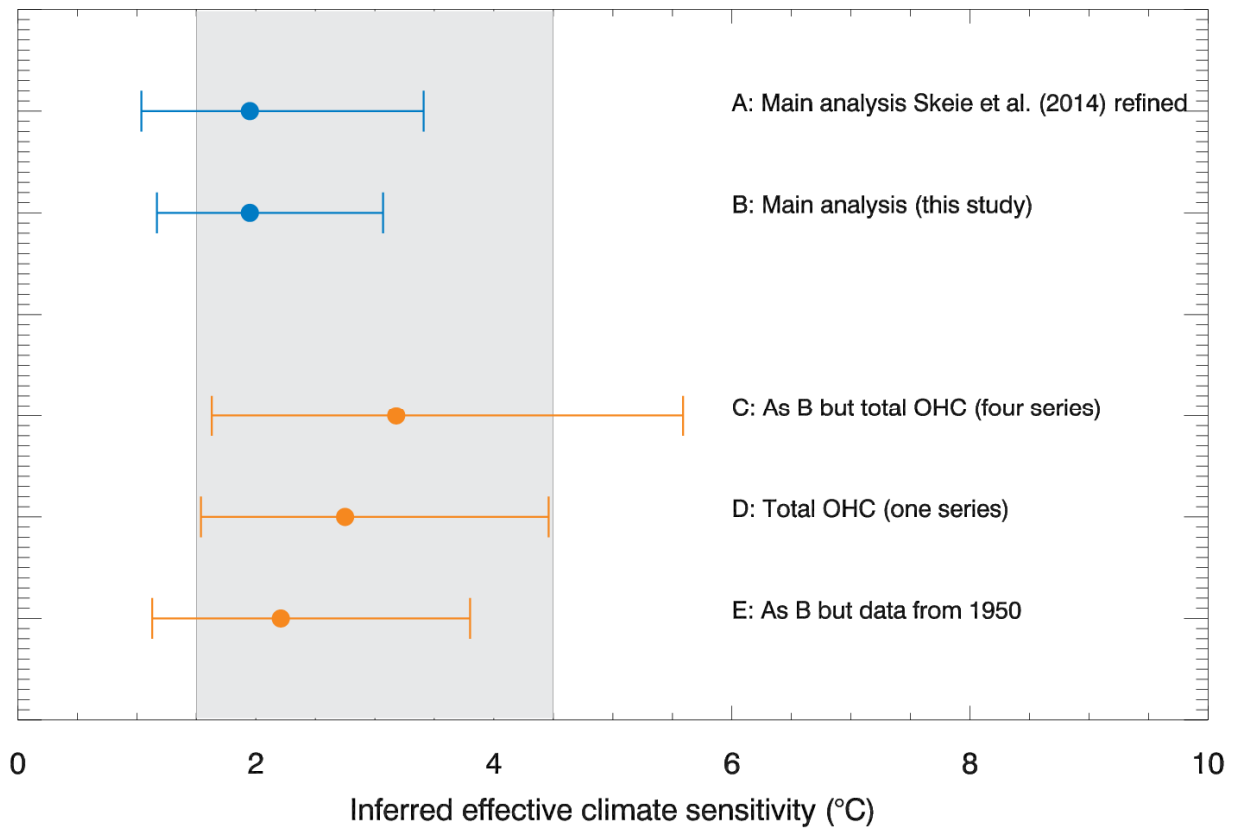
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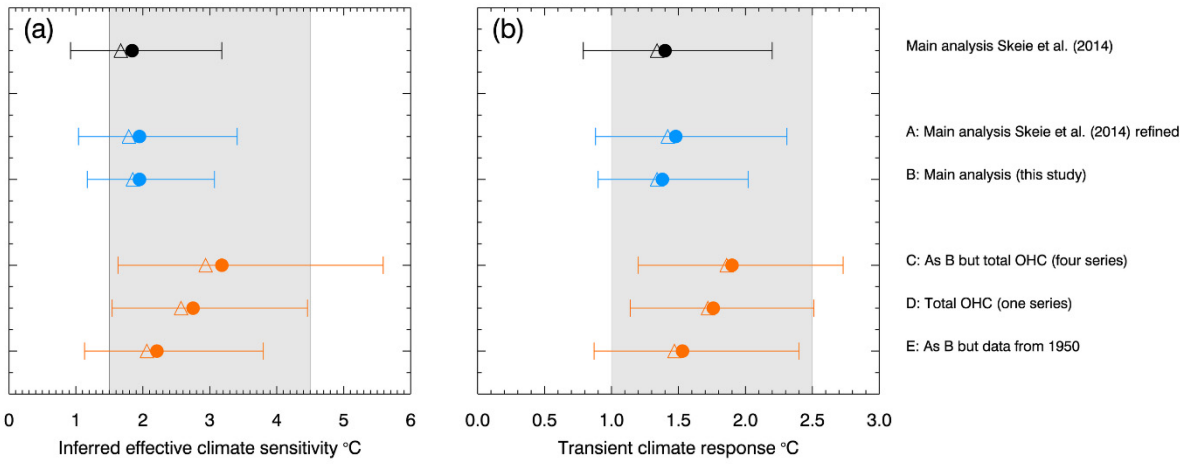
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5 **Figure 1: Posterior 90% C.I. for ECS<sub>inf</sub> (a) and TCR (b) for the different analyses in this study. The estimated posterior mean is indicated by a dot, and the median by an open triangle. The IPCC AR5 likely range (>66% probability) for ECS (a) and TCR (b) is presented as gray shadings. Fig. S2 show the corresponding probability density functions.**

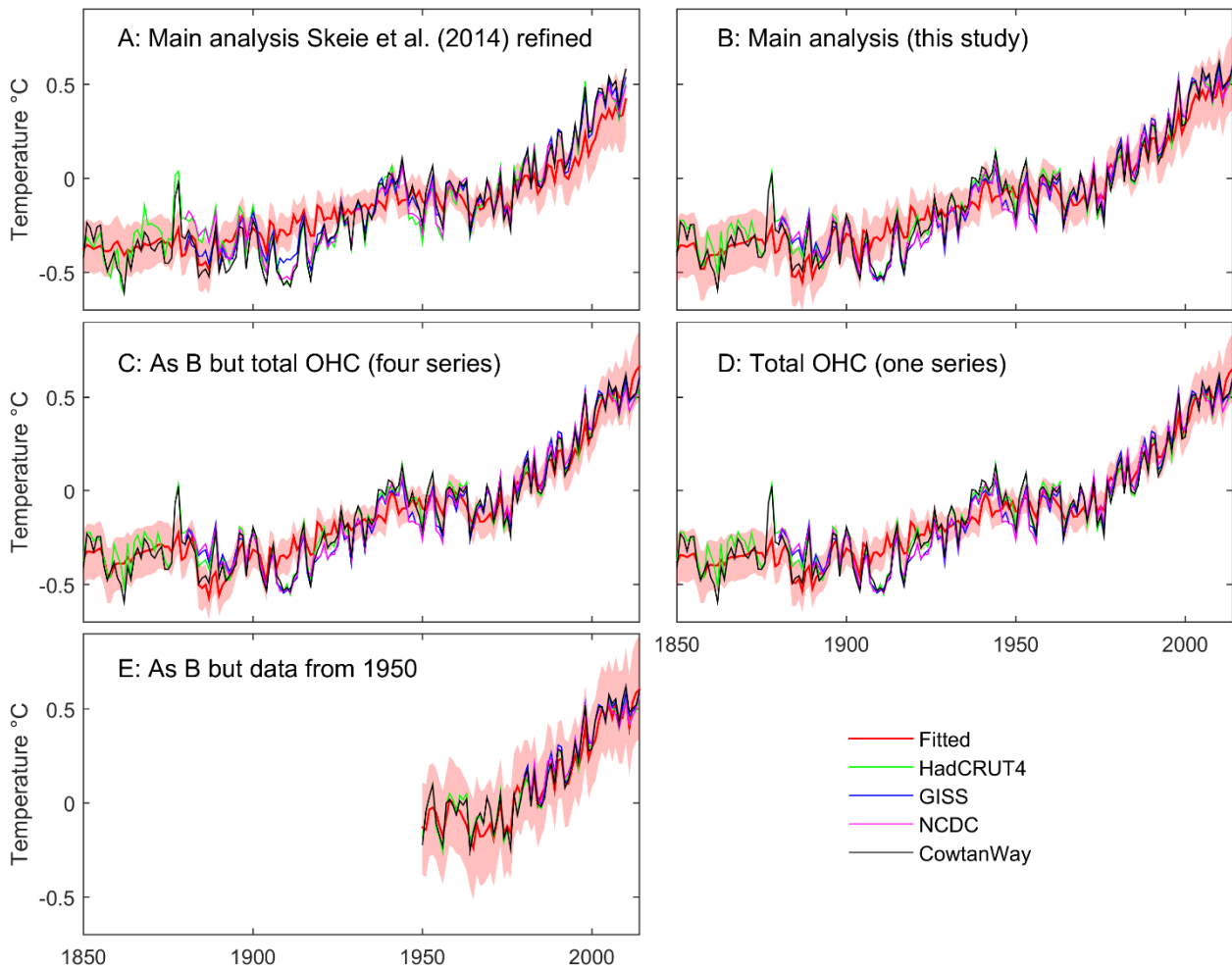


Figure 2: Observed and fitted (posterior mean) values for the GMST. The shaded areas show the 90% C.I. for fitted values i.e. the sum of the output from the deterministic SCM and the short-term internal variability excluding the terms for long-term internal variability and model error. Fig. S3 show three set of fitted values for the GMST for the main analysis that include the long-term internal variability and model error.

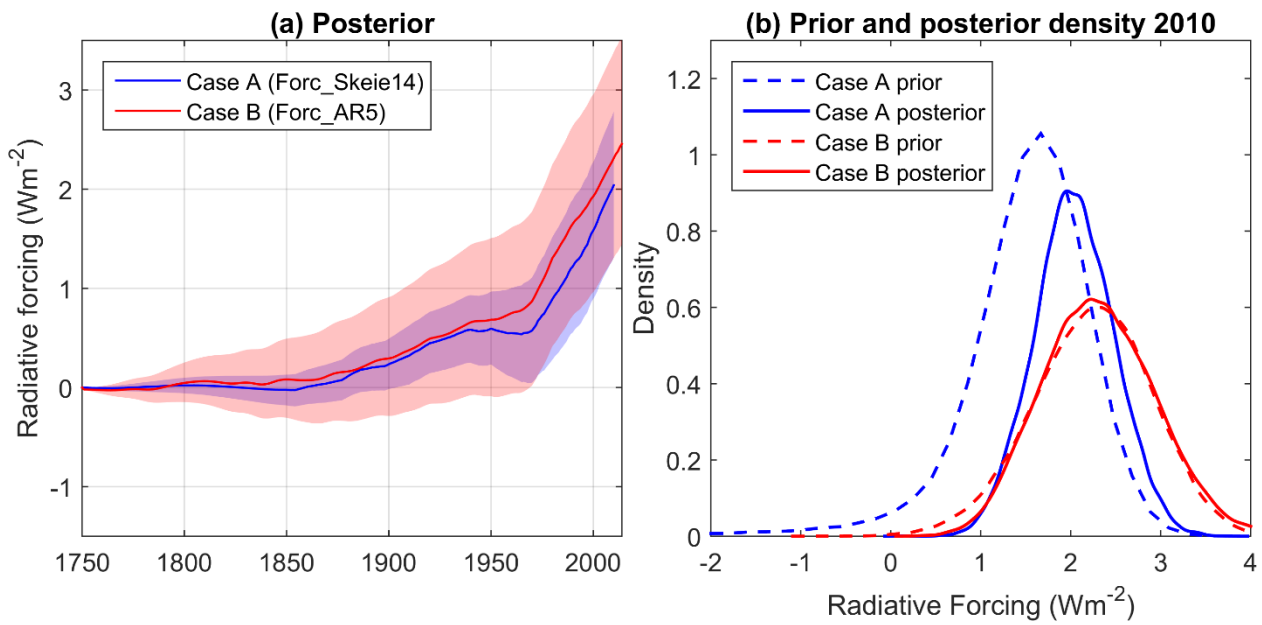
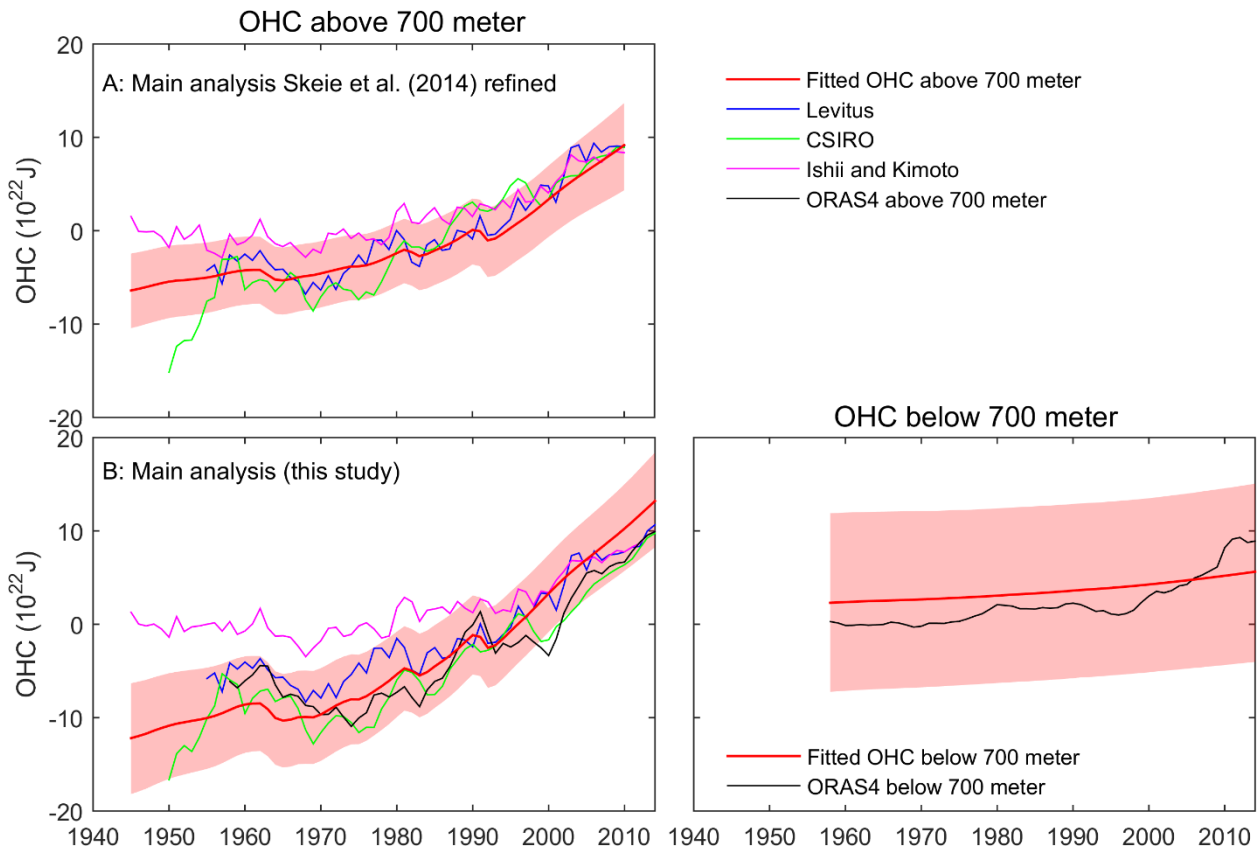


Figure 3: Posterior distribution of time series (a) and prior (dotted) and posterior (solid) probability density function (PDF) in 2010 (b) for anthropogenic forcing. The shaded areas in (a) represent the 90% ~~CI-CL~~.





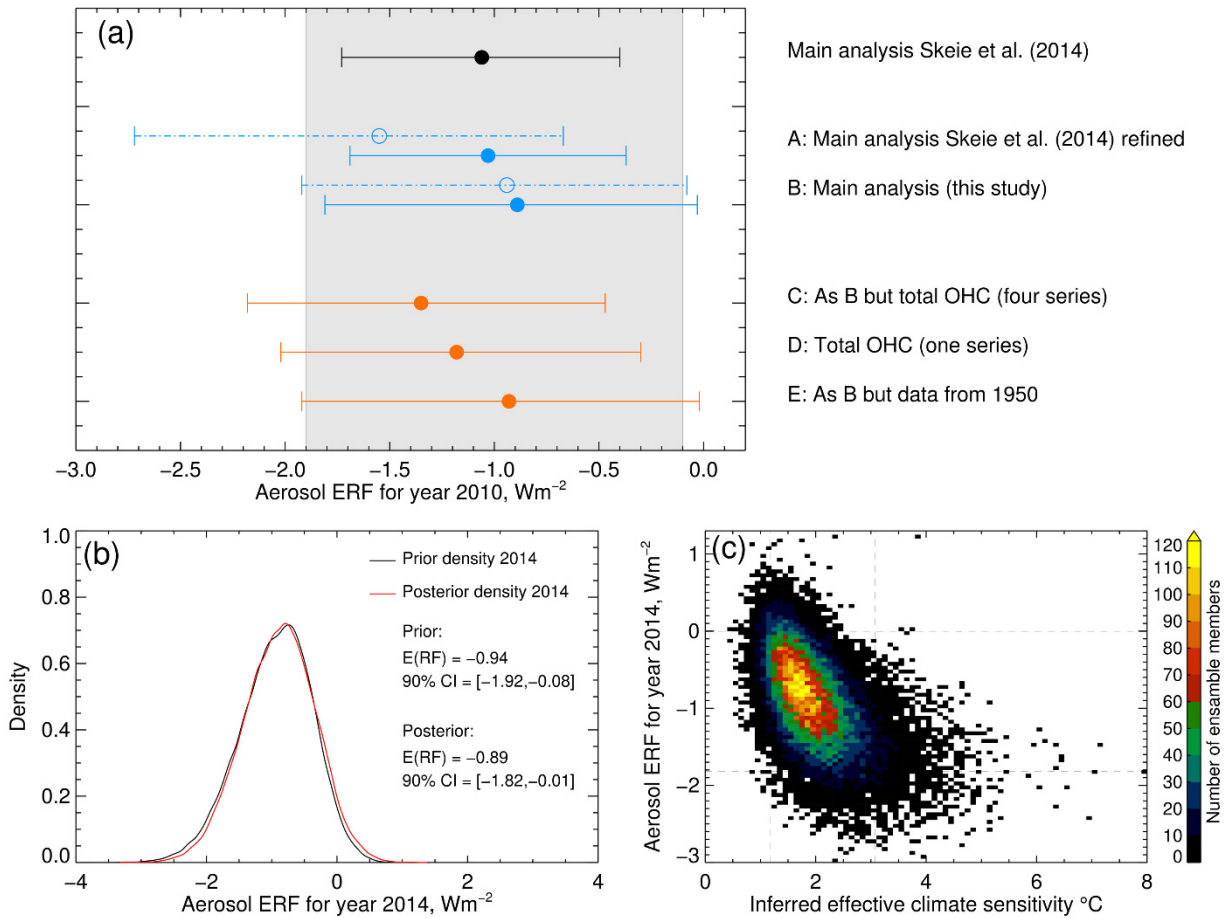
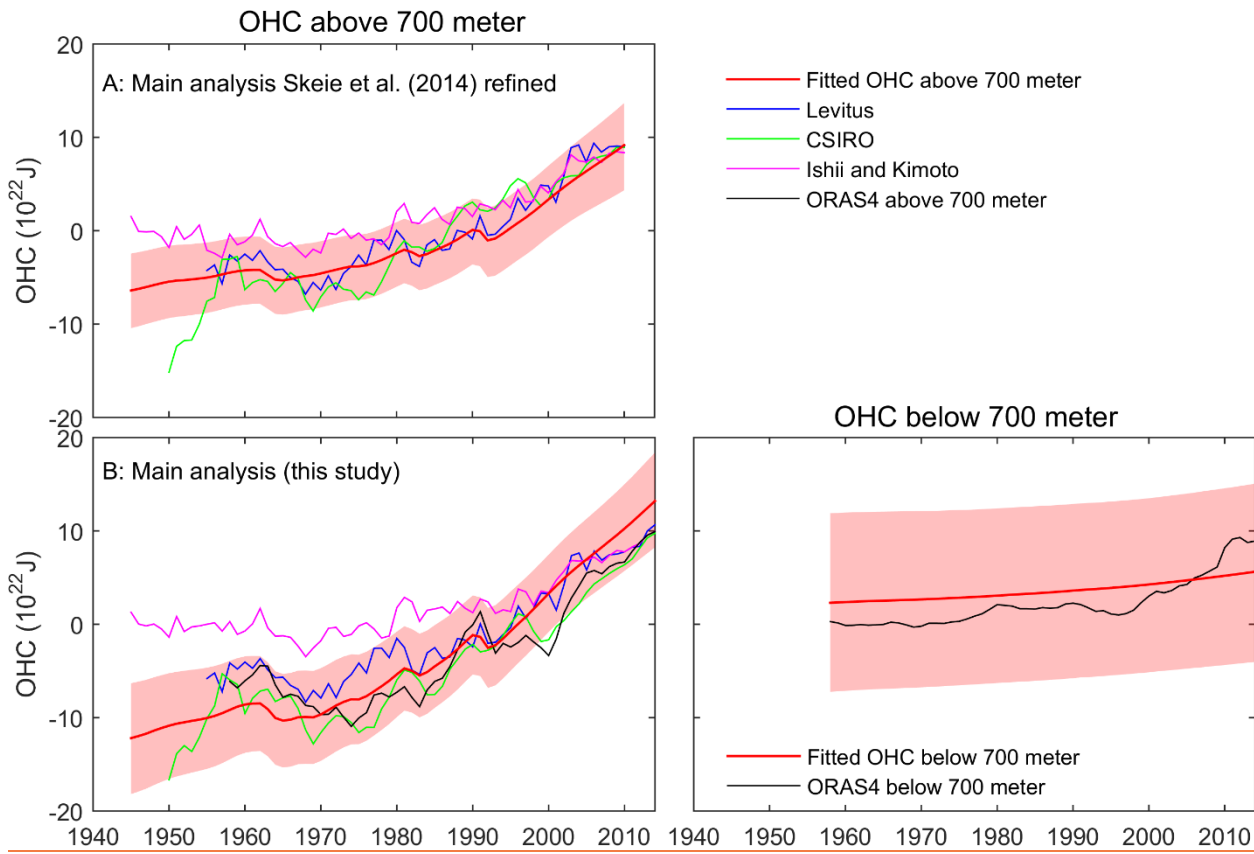


Figure 4: Observed and fitted (Posterior 90% CI for aerosol ERF in 2010 for the different analyses in this study (a). The estimated posterior mean) is indicated by a dot. The two set of priors used is shown as dash-dotted bars with mean value as an open circle. The IPCC AR5 90% probability range for aerosol ERF is presented as gray shadings. The prior and posterior PDF of RF in 2014 the total aerosol effect in case B (b). Red color for the posterior distributions and black lines for the prior distribution. Panel c) show the relationship between  $\text{ECS}_{\text{inf}}$  and aerosol ERF for case B. The posterior 90% CI is indicated by dashed lines.



**Figure 5: Observed and fitted (posterior mean) values for the OHC. The shaded areas indicate the 90% C-4CI. Left column: Upper 700-meter-700m. Right column: Below 700-meter-700m, if data included in the analysis.**

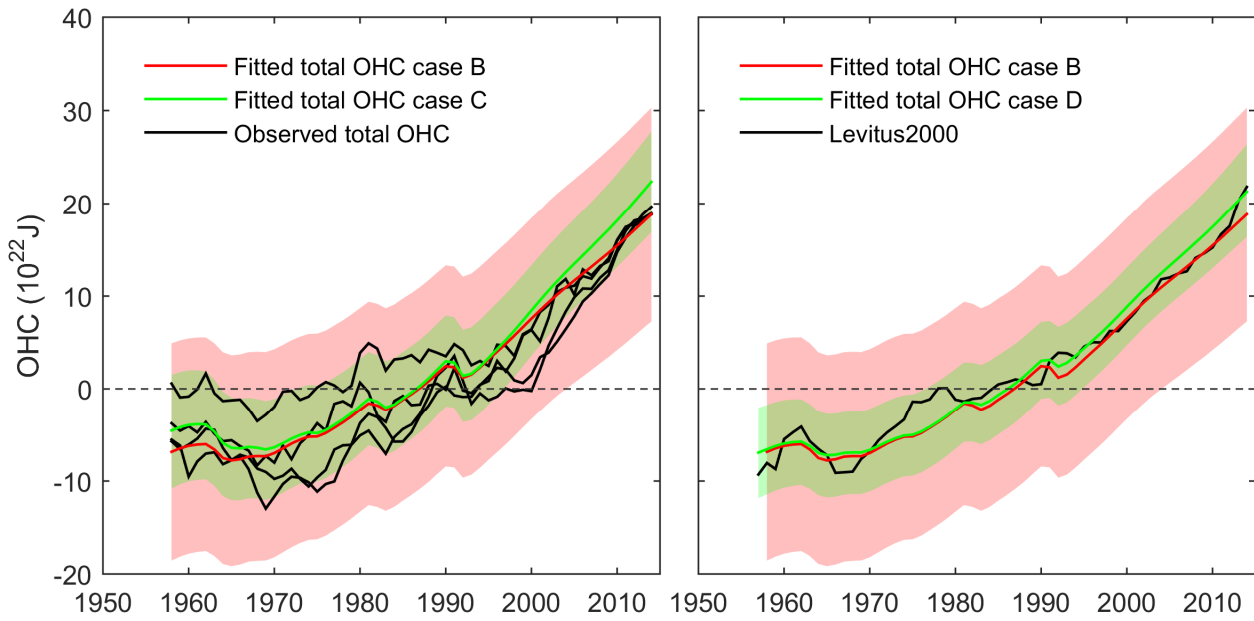
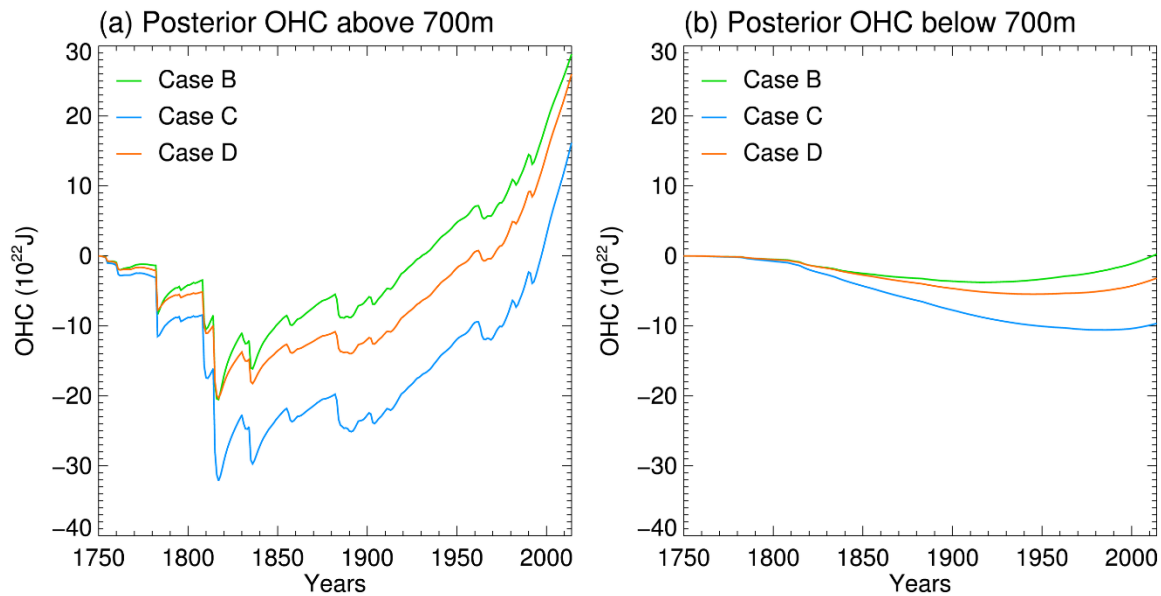


Figure 56: Observed and fitted (posterior mean) total OHC using several OHC dataset (case B and C: separate OHC data above and below 700m and C: merge OHC data above and below 700m, left panel) and using only one dataset for the total OHC (case D, right panel). The shaded areas indicate the 90% CrI.

5



**Figure 7: Posterior mean (solid lines) of the output from the deterministic SCM for OHC above 700m (a) and below 700m (b) for case B, C (total OHC four series) and D (total OHC one series).**

**Table 1: List of data used in the estimation, the abbreviation used in the text, references, in which cases the datasets are used and time of download. The months in parentheses are when data used in case A (see sect. 2.2) were downloaded.**

Abbreviation	References	Dataset used in case	Downloaded
<b>Surface temperature change:</b>			
GISS	(Hansen et al., 2006; Hansen et al., 2010)	<a href="#">A, B, C, D, E</a>	March 2015 (March 2011)
HadCRUT4	(Morice et al., 2012)	<a href="#">A, B, C, D, E</a>	March 2015 (March 2011*)
NCDC	(Smith and Reynolds, 2005; Smith et al., 2008)	<a href="#">A, B, C, D, E</a>	March 2015 (June 2011)
CowtanWay	(Cowtan and Way, 2014)	<a href="#">A, B, C, D, E</a>	March 2015 (April 2014)
<b>Ocean heat content upper 700 <del>meter</del> meters:</b>			
Levitus	(Levitus et al., 2009)	<a href="#">A, B, C, E</a>	March 2015 (March 2011)
CSIRO	(Domingues et al., 2008; Church et al., 2011)	<a href="#">A, B, C, E</a>	April 2014 (October 2011)
Ishii and Kimoto	(Ishii and Kimoto, 2009)	<a href="#">A, B, C, E</a>	March 2015 (October 2011)
ORAS4	(Balmaseda et al., 2013)	<a href="#">B, C, E</a>	March 2015
<b>Ocean heat content below 700 <del>meter</del> meters:</b>			

ORAS4	(Balmaseda et al., 2013)	<a href="#">B, C, E</a>	March 2015
	<b>Ocean heat content above 2000 meters:</b>		
Levitus2000	(Levitus et al., 2012)	<a href="#">D</a>	July 2015
	<b>SOI-index:</b>		
SOI	Southern Oscillation index, Bureau of Meteorology, Australia <a href="http://www.bom.gov.au/climate/current/soihtm1.shtml">http://www.bom.gov.au/climate/current/soihtm1.shtml</a>	<a href="#">A, B, C, D, E</a>	March 2015 (November 2011)
	<b>Forcing time series:</b>		
Forc_Skeie14	(Skeie et al., 2011; Skeie et al., 2014)	<a href="#">A</a>	
Forc_AR5	(Myhre et al., 2013)	<a href="#">B, C, D, E</a>	

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\* HadCRUT3

**Table A1: Variance ratios  $Var_{obs}/Var_{rep}$  for pairwise differences of OHC series.**

<u>OHC series 1</u>	<u>OHC series 2</u>	<u><math>Var_{obs}/Var_{rep}</math></u>
<u>CSIRO</u>	<u>Levitus</u>	<u>0.21</u>
<u>CSIRO</u>	<u>Ishii and Kimoto</u>	<u>0.43</u>
<u>CSIRO</u>	<u>ORAS4</u>	<u>0.17</u>
<u>Levitus</u>	<u>Ishii and Kimoto</u>	<u>2.13</u>
<u>Levitus</u>	<u>ORAS4</u>	<u>3.74</u>
<u>Ishii and Kimoto</u>	<u>ORAS4</u>	<u>3.49</u>