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Analysis of the Model Climate Sensitivity Spread Forced by Mean Sea Surface Temperature Biases

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Abstract

Uncertainties in the numerical realization of the physical climate system in coarse-resolution climate models in the coupled model intercomparison project 3 (CMIP3) cause large spread in the global mean and regional response amplitude to a given anthropogenic forcing scenario and they cause the climate models to have mean state climates different from the observed and different to each other.

In a series of sensitivity simulations with an atmospheric general circulation model coupled to a slab ocean the role of differences in the control mean sea surface temperature (SST) in simulating the global mean and regional response amplitude is explored. The model simulations are forced into the control mean state SST of 24 CMIP3 climate models and 2xCO_2-forcing experiments are started from the different control states. The differences in the SST mean state cause large differences in other climate variables but do not reproduce most of the large spread in the mean state climate over land and ice covered regions found in the CMIP3 model simulations.

The spread in the mean SST climatology leads to a spread in the global mean and regional response amplitude of about 10%, which is about half as much as the spread in the response of the CMIP3 climate models and is therefore of considerable size. Since the SST climatology biases are only a small part of the models mean state climate biases it is likely that the climate model's mean state climate biases are accounting for a large part of the model's climate sensitivity spread.

1. Introduction

The Intergovernmental Panel on Climate Change (IPCC) predictions of the future anthropogenic climate change are essentially based on coarse resolution coupled general circulation models (CGCMs) from the coupled model intercomparison project phase 3 (CMIP3). These simulations predict, depending on the scenario, a substantial global warming with a well defined spatial pattern (e.g. land-sea contrast or polar amplification). While this spatial pattern is well defined for each individual model, the spread from model to model is very large. This is in large part caused by errors in the model formulations [Meehl et al., 2007: Stainforth et al., 2005, Cess et al., 1990, Bony et al., 2006 or Murphy et al., 2004].

The model errors are primarily caused by the uncertainties in the numerical realization of physical processes in coarse-resolution CGCMs. These errors not only cause spread in climate sensitivity, but also cause significant spread in the control mean state climate of these models [Reichler and Kim, 2008]. In a non-linear system, such as the climate system, the sensitivity to external forcing may depend on the mean state of the system. In particular, many important climate feedbacks (e.g. water vapor, cloud cover or snow/ice cover) are directly or indirectly controlled by the surface temperature.

Many studies addressed the role that model mean sate biases play in simulating realistic climate variability or change. The dynamics of the El Nino Southern Oscillation in climate models, for instance, are related to the mean state of the tropical Pacific [Guilyardi, 2006]. Rainfall characteristics in climate models are improved by improved ocean states [Fujii et al., 2009] or atmospheric 'blocking' events in the Northern Hemisphere are related to climate model mean state biases [Scaife et al., 2010]. These internal climate feedbacks are often central for the climate sensitivity as well.

Ashfaq et al. [2011] did a statistical analysis of the relationship between SST biases and climate sensitivity of different climate variables and found that SST biases have substantial impact. Further Senior and Mitchell [2000] and Boer and Yu [2003] analyzed the non-linearity in the climate sensitivity in long integrations. They both find that the global sensitivity changes by about 10-20% due to changes in the local feedbacks caused by changes in the mean state. However, the two different models analyzed showed opposing tendencies.

Statistical analysis of the relationship between climate sensitivity and model mean state biases could not point towards a simple strong relationship between the mean state of a climate model and its climate sensitivity. Some studies, however, find that the mean state errors does give some constraint on the climate sensitivity [e. g. Whetton et al., 2007, Sanderson et al., 2008, Knutti et al., 2010 or Collins et al., 2010].

The results presented in this study aim to explore the role that model mean state biases may play in model climate sensitivity spread. Recent studies that address the causes in model climate sensitivity spread mostly focus on the process uncertainties in the models [Murphy et al., 2004, Stainforth et al., 2005 or Knutti and Hegerl, 2008 for an overview]. Although, some of these studies also discuss a possible influence of the climate mean state biases on the spread in the climate sensitivity, it has to be pointed out that none of these studies really focus on the subject of the mean state climate biases causing climate sensitivity spread in detail. Indeed the model set-ups used in these studies are designed to address model process uncertainties, but does not allow a detailed study of the mean state climate biases influence on the climate sensitivity spread.

In the study presented here an atmospheric general circulation model (AGCM) coupled to a slab ocean model is forced into 25 different SST control climatologies. Starting from these 25 different control climates 2xCO2 response experiments are conducted to explore the role that the different SST control climatologies may play in the global and regional climate sensitivity. The model simulations designed for this study are similar to the concept of Murphy et al. [2004]. They used a series of atmospheric GCM simulations with perturbed physics coupled to a slab ocean model to study the roles of process uncertainties in climate sensitivity spread. They used the flux corrections of the slab ocean model, F_Q, to control the SST climatology in all the different AGCM simulation to be the same as observed. Here we analyze a set of experiments with a single atmospheric GCM coupled to a slab ocean model forced into different mean SST climatologies by state independent flux corrections F_Q, but keeping the AGCM physics the same in all simulations to study the effect of different climate mean states on the climate sensitivity.

The present work is organized as follow: The model simulations that are developed, conducted and analyzed in this article are described in the next section. The analysis sections will start with some discussion on the CMIP3 models mean state climate spread and the climate sensitivity uncertainty on the global and the regional scale in section 3. These findings will be used as the motivation for the main analysis section 4, in which the results of a set of climate change simulations with models that are forced into slightly different mean state control climates are presented. Finally, the analysis sections will be concluded with a discussion of the climate sensitivity spread in flux corrected CMIP3 model simulations. The work will be concluded with a summary and discussions section.

2. Model Simulations and Methods

A list of all simulations discussed in this study is given in Table 1. The CGCM simulations analyzed in this study are taken from the CMIP3 database [Meehl et al., 2007]. All models in the database that have a 20th century control and an A1B 21th century simulations are taken into account for this study, see Table 2. The A1B scenario ensemble was chosen, because it has the largest number of model simulations. These simulations are refereed to as CMIP3 simulations.

Further a set of 12 atmospheric GCM simulations coupled to slab ocean models from the CMIP3 database are analyzed (here refereed to as CMIP3$_{slabs}$). For this ensemble, all simulations in the CMIP3 data base that have a control run and a 2xCO2 scenario run with a slab ocean model are considered in this study. The length of the control and 2xCO2 scenario runs varies between the 12 simulations (see Table 1), but only the first 20yrs of the 2xCO2 scenario run for each model are considered. For each of these 12 CMIP3$_{slabs}$ simulations there is a simulation in the CMIP3 ensemble with the same atmosphere GCM. We will refer to these 12 CMIP3 simulations as the CMIP3$_{reduced\text{-}ensemble}$.

In addition to the simulations of the CMIP3 database an ensemble of simulations with the ECHAM5 atmospheric GCM [Roeckner et al., 2003] in T31 (3.75^{o}x3.75^o) horizontal resolution coupled to a slab ocean model has been conducted for this study (here refereed to as SLAB simulations). The sea surface temperature (SST) is simulated by a simple slab ocean model for open ocean conditions and by a simple thermo dynamical sea ice model for sea ice conditions. The SST for open ocean conditions in the slab ocean model is only forced by the net atmospheric heat fluxes and a state independent flux correction, F_Q. The flux corrections in slab ocean models are, in general, introduce to mimic the mean effect of lateral and vertical ocean dynamics that are not simulated by a slab ocean model, but that are important for the mean SST climatology. In this study will use the fluxes F_Q to force the model into different SST control climate similar to Murphy et al. [2004].

The SLAB set of experiments analyzed consists of 24 simulations, each with a 70yrs long control and a 50yrs long 2xCO_2 simulation. Each control simulation is forced to have one of the 1950-2000 SST climatologies of the 24 CMIP3 simulations in the CMIP3 database from the 20th Century scenario by the state independent flux corrections F_Q to simulate similar SST bias patterns as in the CMIP3 database [Meehl et al., 2007]. The fluxes F_Q needed to produce the control mean SST are computed in an iterative procedure, running the AGCM for 10yrs several times with fluxes F_Q computed from the previous iteration. The control runs are started from the last iteration with the final F_Q fluxes.

The control simulations of these experiments have also been used to study dynamics of El Nino in slab ocean models [Dommenget, 2010]. In addition, a 25th experiment was conducted with a 250yrs long control simulation with the SST forced to be the 24 model ensemble mean SST climatology, from which 5 2xCO_2 simulations were started from 5 different (50yrs apart) initial conditions taken from the control run (here referred to as $SLAB_{CMIP3\text{-}mean}$).

It needs to be noted here that in the following analysis the SLAB ensemble 2xCO_2 simulations are compared with the CMIP3 A1B scenario. The SLAB ensemble is roughly an equilibrium response and the CMIP3 A1B is a transient response. Thus different scenarios are compared, assuming that the characteristics discussed are essentially the same in both scenarios. This is supported by similarity in the response patterns (pattern correlation 0.9). This approach is mainly motivated by limitations in the model database and computing resources. For all the following analysis all model simulations have been interpolated onto a common 3.75°x3.75° global grid. All uncertainties or spreads in the control climate or the response are estimated on the basis of monthly mean climatologies. Thus both the control and the responses are estimated for each model simulation and for each calendar month. The spread in all analysis is always defined by the root mean squared error (RMSE) of the monthly mean values.

3. Analysis of the CMIP3-model simulations

The analysis starts with a look at the CMIP3-models surface temperature, T_{surf}, response and control mean spread. The results will be used as motivation for the subsequent analysis.

The CMIP3-models ensemble annual mean T_{surf} response in the A1B scenario (mean of the period 2070-2099 minus mean of the period 1970-1999) is the well-known pattern shown in Fig. 1a. It is marked by pronounces land-sea warming contrast, a strong polar (Artic) amplification and a global mean warming of about 2.7°K. A similar pattern can be seen in the spread, as quantified by the RMSE, of the control climatological monthly mean T_{surf} of the 24 CMIP3-models; see Fig. 1b. It is also largest over land and sea ice covered regions, but also has some more pronounced spread over some high altitude regions (e.g. Tibet plateau or Antarctica). The spread is much larger than expected from internal variability, which would be in the order of 0.1K for most of the oceans and slightly larger over land and ice regions (see next section for a more detailed discussion of significance).

In the context of this study the most interesting aspect is that the T_{surf} response pattern (Fig. 1a) is similar to the pattern of the mean control T_{surf} spread (Fig. 1b). Thus regions that have large uncertainties in the control mean climate also have a stronger response to increase CO_2 forcing. It is also important to note that the mean control T_{surf} spread is in most regions of similar amplitude as the annual mean T_{surf} response in the A1B scenario (note that the color bars in Fig.1a and b are slightly different). Thus the control mean state climate differences from model to model are in many regions larger than the response signal.

The question arises to what extent does such mean state differences matter. To get a rough zero order idea or a starting point on how important mean state climate differences may be, we can compare the regional difference in the warming response (Fig. 1a) to the regional difference in the mean state climate (not shown): The response ranges by a factor of about 7 (7^oK in the arctic and 1^oK over some ocean regions), while the mean surface temperature, as a proxy of climate differences, varies by about 50^oK (-25^oC in the arctic and $+25^oC$ in the tropics). So we roughly have a 15% change in the regional response amplitude per 1^oK change in local mean state climate. These numbers are comparable to those of the CMIP3 climate model mean state biases and response spread (Fig.1b and c).

The pattern of the T_{surf} response spread (RMSE in Fig. 1c) is also quite similar to both the response pattern itself and to the control mean T_{surf} spread. The response spread has some spatial characteristics beyond a simple scaling of the response pattern, with the strongest relative spread in the higher latitudes, the northern North Atlantic and in the Southern Ocean (Fig.1d). More important for this study is the similarity between the response spread and the control mean state spread (Fig.1b and c). The pattern correlation is 0.85. This however, does not imply any causality yet, as both are indeed caused by model errors and it is for now not clear if the mean state biases cause regional climate sensitivity uncertainty. Indeed, it has to be noted that in most regions there is only a weak (<0.3; in absolute values) linear relationship between the variations of the mean T_{surf} and that of the T_{surf} response (Fig.1e), consistent with previous studies. Some tendencies of a positive linear relationship (warmer mean T_{surf} causes stronger T_{surf} response) exist in the tropics and a more pronounce negative relationship seem to exist in higher latitudes on both hemispheres (Fig.1e).

The above discussion is by no means evidence for the climate model mean state biases having a strong impact on the model climate sensitivity spread, but it is an indication that the different mean state climates may influence the regional and maybe the global climate sensitivity and it is enough motivation to address this issue in more detail. The lack of studies addressing these issues directly with well-designed model sensitivity studies motivated the model simulation designed for this study. In the following analysis it will be argued on the basis of a series of new CGCM simulations that mean state errors, similar to those of the CMIP3 simulations, are indeed large enough to lead to significant spread in the sensitivity to CO_2-forcings.

4. Analysis of the SLAB simulations

We will now discuss the SLAB experiments in which the control mean SST is forced to be in different climatologies, see section 2 for details. For each of the 25 simulations the T_{surf} response is defined as the difference between the last 30 years of the 50years 2xCO2 forcing simulation and the mean of the corresponding 50years control simulation.

First of all it need to be noted that the SLAB simulation mimic the CMIP3-models mean SST climatologies by artificial flux corrections only over open oceans (not over sea ice). Similarity between the SLAB simulations control T_{surf} climatology and those of the CMIP3-models are therefore only expected over open oceans. Fig. 2a and b illustrates how well the SLAB ensemble reproduces the CMIP3 ensemble T_{surf} climatologies in term of their root mean squares errors (RMSE) and anomaly correlation. We can note that the RMSE over open oceans is much smaller than the CMIP3 mean control RMSE (compare with Fig. 1b) indicating a relative good match of the SLAB to the CMIP3 simulation for those regions. This is also quantified by the very high correlation of above 0.9 for most open ocean points. However, it can also be noted that the RMSE is about as strong as the CMIP3 mean control spread (compare with Fig. 1b) over sea ice and land regions and the correlation in those regions is also mostly below 0.4, indicating very little to no agreement between the SLAB and the CMIP3 simulations. Thus the SLAB simulations can only mimic the CMIP3 mean open oceans SST, but do not simulate much of the land and sea ice mean state spread in the CMIP3 simulations. For the following discussion we have to keep in mind that the CMIP3 simulations mean climate spread is largest over land and ice covered regions.

Thus the SLAB simulations only mimic a small part of the total CMIP3 simulations mean climate spread.

The spread within the SLAB ensemble mean control T_{surf} is shown in Fig. 3a. It shows the largest spread in the northern hemisphere sea ice borders. The internal spread is similar to that of the CMIP3 simulation over ocean points, but is much weaker over continental and ice covered regions. As indicated above this reflects that the flux correction of SST only correct a small part of the CMIP3 simulations mean state biases. The largest part of the spread over land and sea ice cover regions is not directly related to the SST mean states spread. Thus the pattern of mean state climate differences in the SLAB ensemble is quite different from that of the CMIP3 simulations (compare with Fig. 1b).

In order to get an understanding of how significantly different to each other the mean state control climates of the SLAB simulations are, the spread within the SLAB ensemble mean control T_{surf} (Fig. 3a) is compared against values of the 99 percentiles of the Students t-distribution shown in Fig. 3b. For the Students t-test the standard deviation is estimated by the standard deviation of annual mean variability of the 250yrs long $SLAB_{CMIP3\text{-}MEAN}$ control simulation. Since we are interested in the response difference over a 30yrs period the t-values are computed for sample sizes N=15, assuming annual mean variability with a lag of 2yrs is independent of the present year, which is justified by the near zero lag-2 correlation. For most regions the 99% value of the Students test is less than 0.4K difference in the 30yrs mean control climate (Fig. 3b). In higher latitudes and on ice regions these values are closer to 1K due to the larger internal natural variability in those regions. If we compare Fig.3a again Fig. 3b we can see that the mean control T_{surf} spread (RMSE) is much larger than the Students t-cumulative distribution 99% values for all parts of the globe, indicating that the difference in the mean climates between the SLAB ensemble members is typically much larger than expect from internal natural variability. This can best be illustrated by plotting the ratio of the SLAB ensemble mean control T_{surf} RMSE (Fig. 3a) divided by the Students t-cumulative distribution 99% values (Fig. 3b), see Fig. 4a. The spread in T_{surf} is beyond the 99% t-value almost everywhere by more than a factor of three. The probability to pass the 99% t-value by that much is less than 0.000002%, indicating that the mean state T_{surf} climatologies of the SLAB ensemble member are indeed quite different from each other.

In the context of climate sensitivity the T_{surf} climate is often not of primary importance, but the focus is more on the climate feedbacks related to atmospheric water vapor, ice-albedo and cloud cover. It is therefore instructive to see how the climate mean state in such variables varies in the SLAB ensemble. We can therefore repeat the significance test, as done for T_{surf} (Fig. 4a), for the other variables as well, see Fig. 4b-f. First of all we can note that the spread of all climate variables analyzed are beyond the 99% t-value everywhere on the globe. The mean sea level pressure (SLP) can be considered as a zero order estimate of the large-scale atmospheric circulation. The significant spread in the SLP can therefore be interpreted as an indication of significant spread in the large-scale atmospheric circulation globally. The surface albedo, which only changes due to changes in snow or ice cover, shows significant spread indicating that the ice and snow cover have substantial mean climate spread over most of the northern hemisphere continents and in particular over sea ice regions. This suggests that ice-albedo feedbacks will have substantial spread in the SLAB ensemble. The same can be concluded from the total cloud cover, which has substantial spread globally. Most importantly the atmospheric vertically integrated water vapor (VIWV) shows quite substantial spread everywhere. Since the VIWV is one of the main factors in the atmospheric greenhouse effect [e.g. Schneider et al., 1999], it seems reasonable to assume that the spread in this variable would lead to a spread in the SLAB ensemble climate sensitivity. In summary the analysis of the SLAB ensemble control climate spread has illustrated that the forced differences in the SST climatology has caused significant spread in the global climate everywhere, in particular in climate variables that are likely to be relevant for the regional and global climate sensitivity.

Fig. 5a shows the SLAB ensemble mean T_{surf} response to $2xCO_2$. The response pattern in the SLAB simulations is similar to that of the CMIP3 ensemble model response to the A1B scenario (see Fig.1a), but larger in amplitude. Fig. 6 shows the difference in the mean T_{surf} response to $2xCO_2$ forcing for each of the 25 SLAB simulations relative to the SLAB ensemble mean response. Only those regions that pass the Students t-value of 99% are shaded. Several important points can be noted here:

- The $SLAB_{CMIP3\text{-}MEAN}$ response is significantly smaller than the SLAB ensemble mean response. Indeed more than 50% of the globe has a much weaker response in $SLAB_{CMIP3\text{-}MEAN}$ simulation. In the global mean response the $SLAB_{CMIP3\text{-}MEAN}$ ensemble is about 9% smaller then the ensemble mean of the SLAB simulations. This is notable, because the $SLAB_{CMIP3\text{-}MEAN}$ simulation has by construction the same mean T_{surf} control climate as the SLAB ensemble. Thus it indicates a non-linearity (see also discussion of Fig. 8 further below). Assuming that the $SLAB_{CMIP3\text{-}MEAN}$ run would represent the 'true' climate mean state, then the ensemble of SLAB simulations, having in average the same mean climate as $SLAB_{CMIP3\text{-}MEAN}$, would still overestimate the response in the ensemble mean average.

- In most of the experiments, more than 50% of the global area is significantly different from the ensemble mean response. Thus we find quite substantial regional difference in the response in most experiments.
- The regional differences have complex spatial structures, with no particular pattern clearly dominating. Thus no single simulation dominates the global mean spread nor is any regional response dominated by one single simulation. In all regions several simulations are found to be significantly different from the ensemble mean.
- There is, however, a tendency for the differences to be of one sign globally, indicating a strong projection onto differences in the global climate sensitivity. The global mean difference explains in average 35% of the total variance for each of the 24 models in the differences shown in Fig. 6.
- Some experiments (e.g. 4, 9, 10, 11, 19 or 22) have a remarkable El Nino like signature in the response difference, which is related to unstable ocean-atmosphere interaction in ACGM coupled to slab ocean models found in several studies [Stainforth et al., 2005 or Dommenget, 2010]. This type of El Nino like variability it different from the observed El Nino dynamics and involves an unstable interaction between the SST and the cloud cover. It leads to the fact the SST in the equatorial Pacific can be quite unstable in slab ocean model simulations for SST climatologies with strong equatorial cold tongues.

The regional spread in the T_{surf} response can again be quantified by the RMSE of the SLAB simulations responses relative to the ensemble mean, see Fig.5b. A few points should be noted from this figure:

- The spread in the response for nearly all regions is much larger than expected from internal variability, which is in the order of 0.3K to 0.8K (99% t-value for oceans and ice regions, respectively, see also Fig. 3b).
- The SLAB ensemble response spread pattern (Fig.5b) is quite similar to the spread in the SLAB ensemble control T_{surf} climatologies (Fig.3a) (pattern correlation of 0.74), but on the other hand the SLAB ensemble response spread pattern is different from that of the CMIP3 ensemble response spread pattern (Fig. 1c). For instance, the larger spread in the SLAB response over the equatorial Pacific and the Sahel region in North Africa (Fig. 5b) seem to match the large spread in the SLAB control climate (Fig. 3a). In turn the large spread in both the mean state climate and the response of the CMIP3 simulations over the Tibet plateau (Fig. 1b and c) is in the SLAB simulations not as pronounce. Thus in both sets of experiments (CMIP3 and SLAB runs), there is an indication of similarity between the mean state spread and the response spread. It seems that the response uncertainties to some degree follow the uncertainties in the mean state.
- The T_{surf} response in the North Atlantic is much less uncertain in the SLAB runs (Fig. 5c) than in the CMIP3 runs (Fig. 1d). This is most likely related to the missing ocean dynamics in the SLAB runs, that cannot simulate the slowing down of the thermohaline circulation in the northern North Atlantic as found in most CMIP3 simulations.

- The southern ocean response appears to be quite uncertain in both the CMIP3 and the SLAB ensemble, despite very different ocean dynamics in the two ensembles, indicating that ocean dynamics may not be the dominating factor contributing to the uncertainty in the CMIP3 ensemble. The uncertainties in the sea ice distribution are factors that lead to the relative large uncertainties in this region in the SLAB ensemble. In contrast to the North Atlantic the Southern ocean does not have a strong circulation response, that influences the SST response substantially, which may explain why the over all structure of the uncertainties is the same in both ensembles.

The local correlation between the SLAB variability of the T_{surf} mean state and response is, as in the CMIP3 runs, mostly zero, but again negative in the higher latitudes (Fig.5d). The stronger negative correlation in the equatorial Pacific, may be related to the slab ocean El Nino dynamics [Dommenget, 2010], which as such do not exist in CGCMs (the CMIP3 runs) or are at least much less dominant. Further it has to be noted that the variations in the 24 CMIP3 T_{surf} responses have only weak correlation to the variations in the 24 SLAB responses with the matching SST climatology, indicating that the variations in the 24 CMIP3 T_{surf} responses are not reproduced by the SLAB simulations, see Fig.5e.

We can now focus on the spread in the global mean T_{surf} sensitivity. To illustrate the spread in the response caused by the spread in the mean SST, it is instructive to compare the spread of the global mean T_{surf} response time series with those caused by internal variability only. Therefore Fig.7a and b show the anomaly time series of global mean T_{surf} of each SLAB control and 2xCO2 scenario run. In the 24 SLAB simulations the spread in the response time series is clearly increased compared to the internal variability in the control runs (Fig.7b). In contrast the spread due to internal climate variability in the 5 $2xCO_2$ responses of $SLAB_{CMIP3\text{-}MEAN}$ (Fig.7a) is much smaller and not increased compared to the control runs. Thus it is clear that the mean state spread in the control SST causes a substantial global mean T_{surf} sensitivity spread.

The spread in the global mean and regional response in the ensembles of the CMIP3 and SLAB simulations can be summarized by plotting the normalized regional response difference from the ensemble mean[2] against the global mean response difference from the corresponding ensemble mean of each model normalized by the corresponding ensemble mean responds, see Fig. 8. The x-axis indicates by how much each model deviates from the ensemble mean response at any grid point at any calendar month in average. It thus estimates how similar the response patterns are. The values are in percentage of the ensemble mean respond. A value of 0% would indicate a response pattern identical to the ensemble mean response pattern and a value of 100%, for instance, would indicate that the response difference from the ensemble mean response pattern is on average over all locations and calendar months as big as the mean amplitude of the ensemble mean response pattern and would therefore mark a quite substantial difference in the response pattern. A few important characteristics should be pointed out here:

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[2] The uncertainty in the local response amplitude can be estimated by the normalized response pattern RMS-error of each model relative to the normalized CMIP3 ensemble mean response pattern:

$$\sigma_i = \sqrt{\sum_{m=1}^{12} \sum_{x,y} w(x,y) \cdot \left(\frac{T_i(m,x,y)}{\hat{T_i}} - \frac{T_{ensemble}(m,x,y)}{\widehat{T_{ensemble}}}\right)^2 /12}$$

With the T_{surf} response of climatological month, m, the individual Models, $T_i(m)$, and that of the CMIP3 ensemble mean, $T_{ensemble}(m)$, and their respective global means, $\hat{T}_i(m)$ and $\hat{T}_{ensemble}(m)$. The normalized response pattern RMS-error of each model, ε_i, gives a measure of the relative uncertainty of the local response amplitudes, independent of the global mean response.

- The uncertainties in the global mean and regional response of the 5 members $SLAB_{CMIP3\text{-}MEAN}$ ensemble give an indication of uncertainties caused by internal natural variability. The spread in the regional response is about 8% due to regional modes of internal variability. The spread in the global mean is only about 0.5% (the standard deviation of the points along the y-axis) and thus much smaller than regional uncertainties, because modes of natural variability are much smaller on the global mean than they are on regional scales.
- The global mean and the regional response spread are much larger in the SLAB and CMIP3 model ensembles than in the $SLAB_{CMIP3\text{-}MEAN}$ ensemble, indicating that the variations in the SST climatologies in these ensembles cause the large response spreads.
- The regional response spread due to variations in the SST climatologies in the 24 SLAB is 11% to 24% relative to the ensemble mean response pattern, while the 24 CMIP3 models spread is about 22% to 43%. Thus the regional response spread in the SLAB ensemble is almost half as big as in the CMIP3 ensemble.
- The global mean response spread (standard deviation of the points) is about 10% in the SLAB ensemble and 20% in the CMIP3 ensemble. Thus the SLAB ensemble spread in the global mean is about 1/2 of the CMIP3 spread.
- Both, the SLAB and CMIP3 distributions of the global climate sensitivity are positively skewed (0.9 for the SLAB and 0.8 for the CMIP3 ensemble). Considerations with simple feedback models find similar results [Roe and Baker, 2007]. This is also consistent with the previous discussion of Fig.

6a, saying that the sensitivity from the $SLAB_{CMIP3\text{-}MEAN}$ simulations is weaker than the mean sensitivity of the SLAB ensemble.

5. Flux corrected climate models

The control SST mean state spread in the SLAB runs lead to a significant spread in the global and regional climate sensitivity. If we further consider that the T_{surf} spread over land or ice regions or other important climate variables (e.g. mean cloud cover, sea ice distribution or mean atmospheric or oceanic circulation) are not accounted for in the SLAB experiments, then it seems likely that the overall control climate spread in the CMIP3 runs could lead to an even larger spread in the regional and global climate response of the CMIP3 scenarios. The question arises: How does this relate to the fact, that the climate sensitivity spread in the climate models of the past decades, which did include climate models with flux corrections to control the climate mean state, was as strong as it is in today's, uncorrected, CMIP3 climate models? Thus indicating, that mean state corrections may not improve the models at all.

The flux corrections introduced in climate models in the 1980s to 1990s are in principle similar to those flux corrections used in the SLAB simulations. These were meant to reduce the errors in the SST climatologies due to the limitations of the coupled ocean-atmosphere model simulations. As in the SLAB ensemble these flux corrections could only reduce the spread in the SST over open oceans, but not over land or sea ice covered regions.

To get some understanding of how much flux corrections of the SST in CMIP3 models can change the mean state spread and the response uncertainty, we can take a look at 12 flux corrected slab-ocean simulations of the CMIP3 database, *CMIP3$_{slab}$*. Fig. 9 illustrates a few statistics that correspond to those we discussed above for the CMIP3 and SLAB ensemble. A few important points can be made from these statistics:

- Flux correction of the SST does not reduce the control mean surface temperature spread over land or ice cover regions by any substantial amount (compare Fig.9a with Fig.1b). Indeed even the SST mean state is substantially different between the different models, despite the fact that all simulations include flux corrections towards the same observed mean SST. Some of these SST mean state errors are caused by tropical unstable ocean-atmosphere interactions between the SST in very strong equatorial Pacific cold tongues and the cloud cover, which is a prominent signature in some slab ocean models [Stainforth et al., 2005 and Dommenget, 2010]. Substantial impact from a corrected mean state climate onto the climate sensitivity, would most likely only be achieved if the surface temperature over land and sea ice covered regions are corrected as well, as these regions contributed to the mean state climate spread the most. This has so far never been tested.
- The comparison between the response spread in the *CMIP3$_{slab}$* runs with the reduced ensemble of CMIP3 CGCM including the same atmosphere models, *CMIP3$_{reduced\text{-}ensemble}$*, shows that the regional relative response spread is indeed reduced to globally 28%(Fig.9c) in the *CMIP3$_{slab}$* runs form 31%(Fig.9d) in the *CMIP3$_{reduced\text{-}ensemble}$* runs and even more over tropical oceans (to 22% from 27%). Although these differences are

relatively small we can try to estimate if they are consistent with what we would expect if the SST mean control climate has an influence on the response as the results with the SLAB runs suggest. We can, as a crude first order approximation, assume that the regional climate sensitivity spread globally averaged, δ_{total}, (31%; Fig.9d) is the sum of two independent parts: one being the spread caused by SST mean state biases, δ_{SST}, which is roughly estimated by the SLAB ensemble (16%; Fig.5c). The other, δ_{rest}, is caused by all other uncertainties (including all process uncertainties and mean state errors in all other climate fields not directly related to the SST). It is almost certain that the two parts are not independent, but as the relationship is not known and a potential relationship could either increase or decrease the spread, we have to live with the crude assumption of independence just for the sake of a first guess. The sum of independent errors ($\delta_{total}^2 = \delta_{SST}^2 + \delta_{rest}^2$) would suggest δ_{rest} = 27%. This is comparable with the 28% found in the relative response spread in Fig.9c. Although these results are consistent with the hypothesis that the mean state spread may cause climate sensitivity spread, it need to be noted that this is not a completely consistent comparison, as the set $CMIP3_{reduced\text{-}ensemble}$ includes uncertainties from ocean dynamics that are not included in the $CMIP3_{slab}$ set and on the other hand δ_{SST} is certainly not zero in the $CMIP3_{slab}$ runs.

In summary, current or past flux corrected climate models did not allow for much reduction in climate sensitivity uncertainty, as they only correct ice–free oceans SSTs and even that error is not reduce to zero. So conclusions drawn from these flux correct models are limited: They can neither strongly support the idea of the mean state biases contributing significantly to the climate sensitivity uncertainty (although they are consistent with these hypothesis) nor can they reject this idea.

6. Summary and Discussion

In this study we addressed the question of whether the SST mean state spread, as present in the current CMIP3 simulations, could have an impact on the climate sensitivity of the models. The analysis started with some discussion of the characteristics of the regional climate sensitivity and the control mean T_{surf} spread in the CMIP3 model simulations. In this analysis some remarkable similarities between the mean control climate spread pattern, the response and the pattern of the spread in the response of the models in the A1B scenario are found.

The main analysis of this study focused on a set of AGCM simulations with a coupled flux corrected slab ocean model. In these SLAB experiments the model is forced into different SST mean control climatologies from which 2xCO_2 response experiments are started. The SST climatologies closely match those of the 24 CMIP3 model simulations of the 20th century. The main findings of these experiments can be summarized as follows:

- Differences in the SST control mean climatology lead to quite significant differences in the control climate globally in many different important climate variables (e.g. vertically integrated water vapor, cloud cover or snow/ice cover) that change feedbacks in the climate system important for the response to CO_2 forcing.

- The flux correction of open ocean SSTs only controls T_{surf} over open oceans, but almost not at all over land or ice covered regions. Subsequently SST flux corrected models still have an almost unchanged spread in the control mean T_{surf} climatologies over land and ice covered regions.
- The global and regional response to 2xCO_2 forcing is significantly altered by the different SST climatologies. The spread is almost half as strong as in the 24 CMIP3 A1B-scenarios.
- Considering that the T_{surf} spread over land or ice regions or other important climate variables (e.g. mean cloud cover, sea ice distribution or mean atmospheric or oceanic circulation) are not accounted for in the SLAB experiments, then it seems likely that the overall control climate spread in the CMIP3 runs could account for a substantial, if not the largest part, of the regional and global climate response spread of the CMIP3 scenarios.

The SLAB simulations suggest that differences in the SST mean state of the CMIP3 models could cause a spread in the global and regional T_{surf} response of about 10%, which is comparable in strength to the climate sensitivity changes found by Senior and Mitchell [2000] and Boer and Yu [2003] in analyzing the non-linearities in the climate sensitivity caused by changes in the mean climate and associated feedback during long transient runs. However, two important differences to these two studies should be pointed out here: First the SLAB simulations only consider changes in SST, but neglected changes over land and ice regions. Thus the SLAB experiments would suggest that the spread in the response by the total climate mean state uncertainties would be significantly larger. Second, the patterns of mean control climate differences between the models are quite different from the global warming pattern. While Boer and Yu [2003] find that the changes in the mean climate by the global warming pattern affect the climate sensitivity, it is unclear how much the climate sensitivity would change due to other patterns. The results of the SLAB simulations have illustrated that different climate mean state biases have different effects on the climate sensitivity.

The results of this study open up the question: Do climate models forced into the observed mean state climate (e.g. in T_{surf} over land, oceans and sea ice covered regions), by some kind of artificial corrections, produce a more realistic and less uncertain climate sensitivity? The answer cannot be given in this study. However, significant improvement of climate models by better representation of physical processes will take many years to decades. On the other hand a coupled climate system model can be more than just the sum of its parts (e.g. cloud model, land model, ocean model, sea ice model, convections scheme, etc.). It may be possible to improve coupled climate models without improving any individual sub system of the coupled system, but by improving the strategy of coupling the subsystems together. Considering the importance of the correct mean state climate, as this present study suggest, it may be worth considering new strategies of coupling the subsystems by some kind of anomaly or mean state climate linearization strategies. Such strategies could enforce that each subsystem of the coupled climate model system sees in average realistic observed mean state conditions and would therefore potentially produce tendencies in response to CO_2 forcing that are closer to how the real world would respond, than they would be if they see model biased mean state conditions. In non-linear systems, such as our climate, the correct mean state condition is important for producing the correct tendencies to external forcings. Such an approach has so far not been tested in the context of CGCMs, but the results presented in this study suggest that it may be worthwhile to explore such methods.

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Figures

Figure 1: (a) CMIP3 ensemble mean response in the A1B scenario (period 2070-2099 minus 1970-1999); (b) Root mean squared error (RMSE) of the 24 CMIP3 simulations monthly mean T_{surf} climatologies relative to the CMIP3 ensemble mean T_{surf} climatology from 1970-1999. (c) RMSE of the 24 CMIP3 simulations monthly mean T_{surf} response in the A1B scenario (mean 2070 to 2099 minus mean 1970-1999) relative to the CMIP3 ensemble monthly mean T_{surf} response as shown in (a). (d) the relative response spread defined as: the result in (c) divided by the results in (a). (e) Correlation between the 24 monthly mean climatologies and the responses. Anomalies for the climatologies are defined in the same way as for (b) and for the responses they are defined in the same way as for (c). Numbers in the headings are the global mean values.

Figure 2: (a) RMSE between the 24x12 monthly mean T_{surf} climatologies of the SLAB and CMIP3 ensemble. (b) correlation for the same data as in (a).

Figure 3: (a) Root mean squared error (RMSE) of the monthly mean T_{surf} control climatologies as Fig. 1b, but for the 24 SLAB experiments over the last 50yrs of the 70yrs control run relative to the 24 SLAB ensemble mean climatology. (b) the 99% values of the cumulative Students t-distribution, testing for a difference in the mean of a 30yrs period based on the 250yrs $SLAB_{CMIP3\text{-}MEAN}$ control annual mean T_{surf} variability assuming 15 independent values in the 30yrs period.

Figure 4: (a) The ratio of the RMSE of the control mean for T_{surf} climatology (Fig. 3a) divided by the 99% t-value (Fig. 3b). (b) to (f) as (a) but for (b) SLP, (c) surface albedo, (d) cloud cover, (e) vertically integrated water vapor and (f) for precipitation. Surface albedo values are undefined (grey shading) for regions that did not had any surface albedo variability in the 250yrs $SLAB_{CMIP3\text{-}MEAN}$ control simulation.

Figure 5: (a) the 24 SLAB ensemble mean response in the $2xCO_2$ simulations (last 30yrs of the 50yrs $2xCO_2$ run minus control mean); (b) response RMSE as in Fig. 1c, but for the 24 SLAB experiments response over the last 30yrs of the 50yrs 2xCO2 experiment relative to the SLAB ensemble mean response. (c) the relative response spread as in Fig. 1d, but for the SLAB experiments. (d) Correlation between the 24 monthly mean climatologies and the responses as Fig. 1e, but for the 24 SLAB experiments. (e) correlation between the 24x12 monthly mean climatological responses of the SLAB and the CMIP3 ensemble (responses defined as in (a) and Fig. 1c).

Figure 6: (a) $SLAB_{CMIP3\text{-}mean}$ T_{surf} response difference relative to the SLAB ensemble mean response (as shown in Fig. 5a). Panels (b)-(y) as (a) but for each of the 24 SLAB ensemble members. Shading indicates regions with the T-test value beyond the 99% confidence interval.

Figure 7: (a) global mean T_{surf} time series of the 5 $SLAB_{CMIP3\text{-}mean}$ control and $2xCO_2$ simulations relative to the control global mean. The shaded regions mark the interval of ± 2 standard deviations of the control (blue) and $2xCO_2$ (red)

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Figure 8: Scatter plot of the CMIP3 models climate sensitivity for the A1B-scenario (blue circles). The x-axis shows a measure of regional differences in the warming pattern in percentage of the corresponding ensemble mean response. It is an estimate of the mean local response amplitude deviation from the CMIP3-ensemble mean response; see text for a definition. The y-axis shows the global mean T_{surf} response difference in percent relative to the corresponding ensemble mean. The corresponding scatter plot is done for the 24 SLAB simulations (red triangles) relative to the 24 SLAB ensemble mean response and for the 5 $SLAB_{CMIP3\text{-}mean}$ simulations (green crosses) relative to the 5 $SLAB_{CMIP3\text{-}mean}$ ensemble mean response. The responses for both the CMIP3 and the SLAB ensembles are computed as in Fig. 1 and Fig. 5, respectively.

Figure 9: (a) the RMSE of the 24 $CMIP3_{slabs}$ simulations monthly mean T_{surf} control climatologies relative to the $CMIP3_{slabs}$ ensemble mean T_{surf} climatology. (b) the RMSE of the 24 $CMIP3_{slabs}$ simulations monthly mean T_{surf} response averaged over the year 11 to 20 relative to the $CMIP3_{slabs}$ ensemble mean response. (c) as (b) but divided by the $CMIP3_{slabs}$ ensemble mean response. (d) as in (c) but for the $CMIP3_{reduced\text{-}ensemble}$.

Tables

Table 1: List of simulations discussed in this study.

Name	Number of runs	Scenarios (number of years)	Model type	Comment
CMIP3	24	20^{th} (100yrs) +A1B(100yrs)	CGCM	
$CMIP3_{reduced-ensemble}$	12	20^{th} (100yrs) +A1B(100yrs)	CGCM	The subset of the CMIP3 ensemble that has the matching AGCM to the $CMIP3_{slabs}$ ensemble.
$CMIP3_{slabs}$	12	Control (30yrs to 150yrs) + 2xCO2 (20yrs)	AGCM-slab	Length of control varies
SLAB	24	Control (70yrs) + 2xCO2 (50yrs)	AGCM-slab	Control mean T_{surf} matching the CMIP3 ensemble.
$SLAB_{CMIP3-mean}$	1 control 5 2xCO2	Control (250yrs) + 5 times 2xCO2 (50yrs)	AGCM-slab	Control mean T_{surf} matching the CMIP3 ensemble mean.

Table 2: CMIP3 model simulations. The experiment numbers correspond to those used in the analysis of the SLAB simulations.

Experiment number	CMIP3-model Name
1.	BCCR BCM 2.0
2.	CCCMA 3.1 (T63)
3.	CCCMA 3.1
4.	CNRM 3
5.	CSIRO MK3.0
6.	CSIRO MK3.5
7.	GFDL 2.0
8.	GFDL 2.1
9.	GISS AOM
10.	GISS E-H
11.	GISS E-R
12.	IAP FGOALS 1.0g
13.	INGV ECHAM4
14.	INM 3.0
15.	IPSL 4
16.	MIROC 3.2 hires.
17.	MIROC 3.2 medres.
18.	MIUB ECHO-G

19.	MPI ECHAM5
20.	MRI 2.3 2a
21.	NCAR CCSM 3.0
22.	NCAR PCM 1
23.	UKMO HAD 3
24.	UKMO HADGEM 1

Figure 1

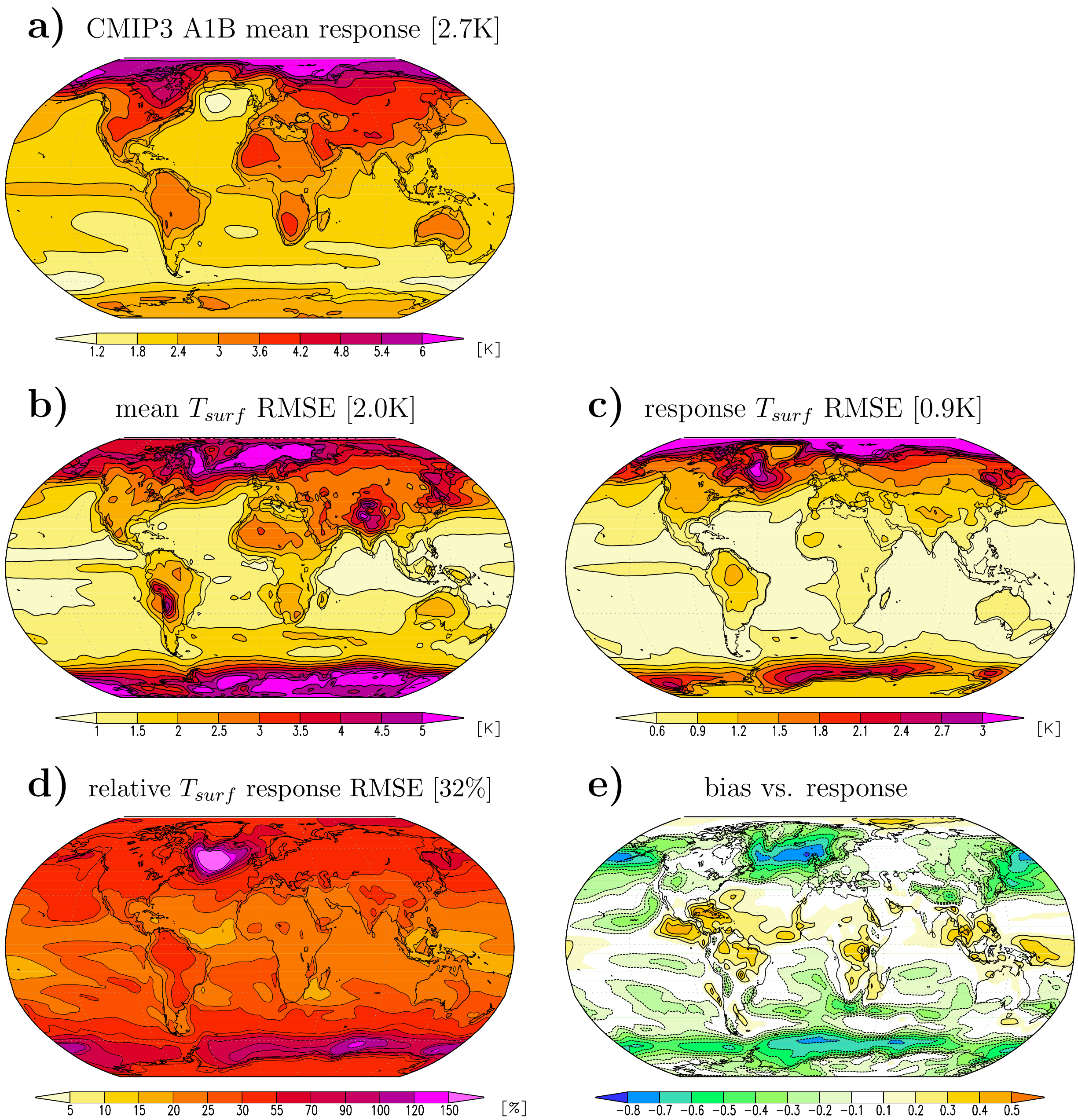

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Figure 2

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Figure 2

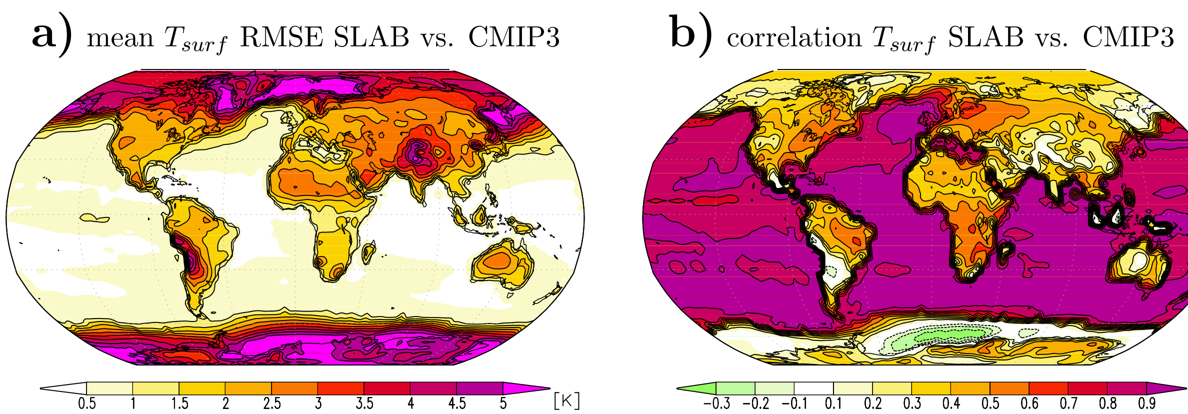

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Figure 3
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Figure 3

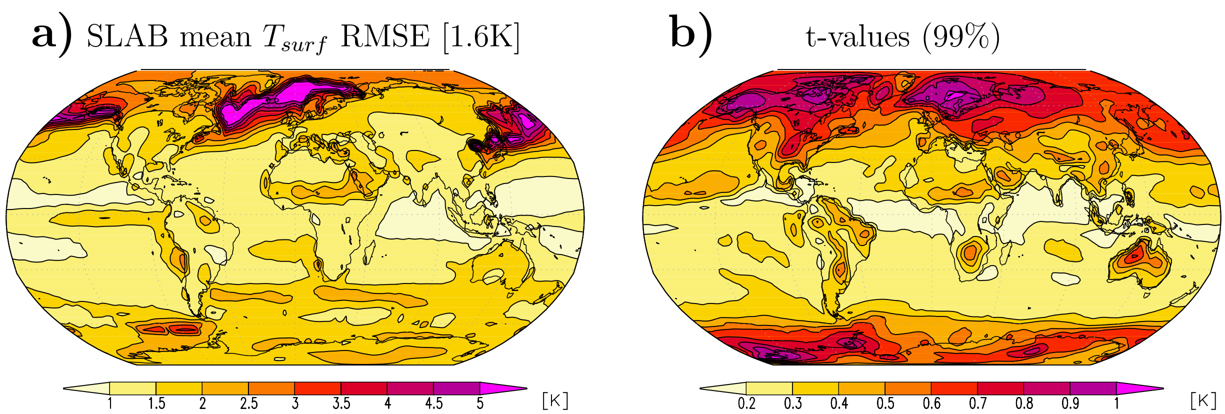

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Figure 4

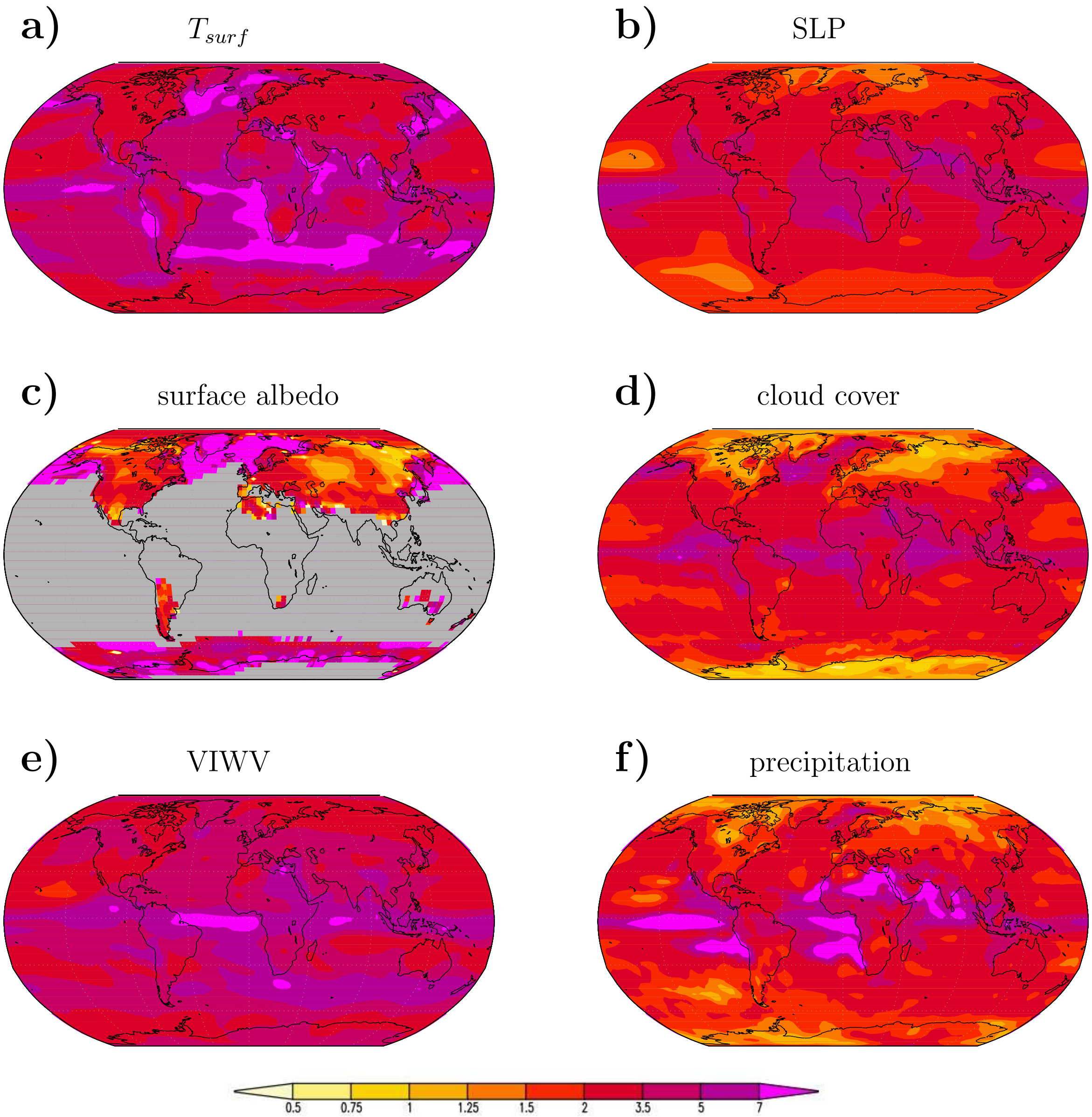

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Figure 5

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Figure 5

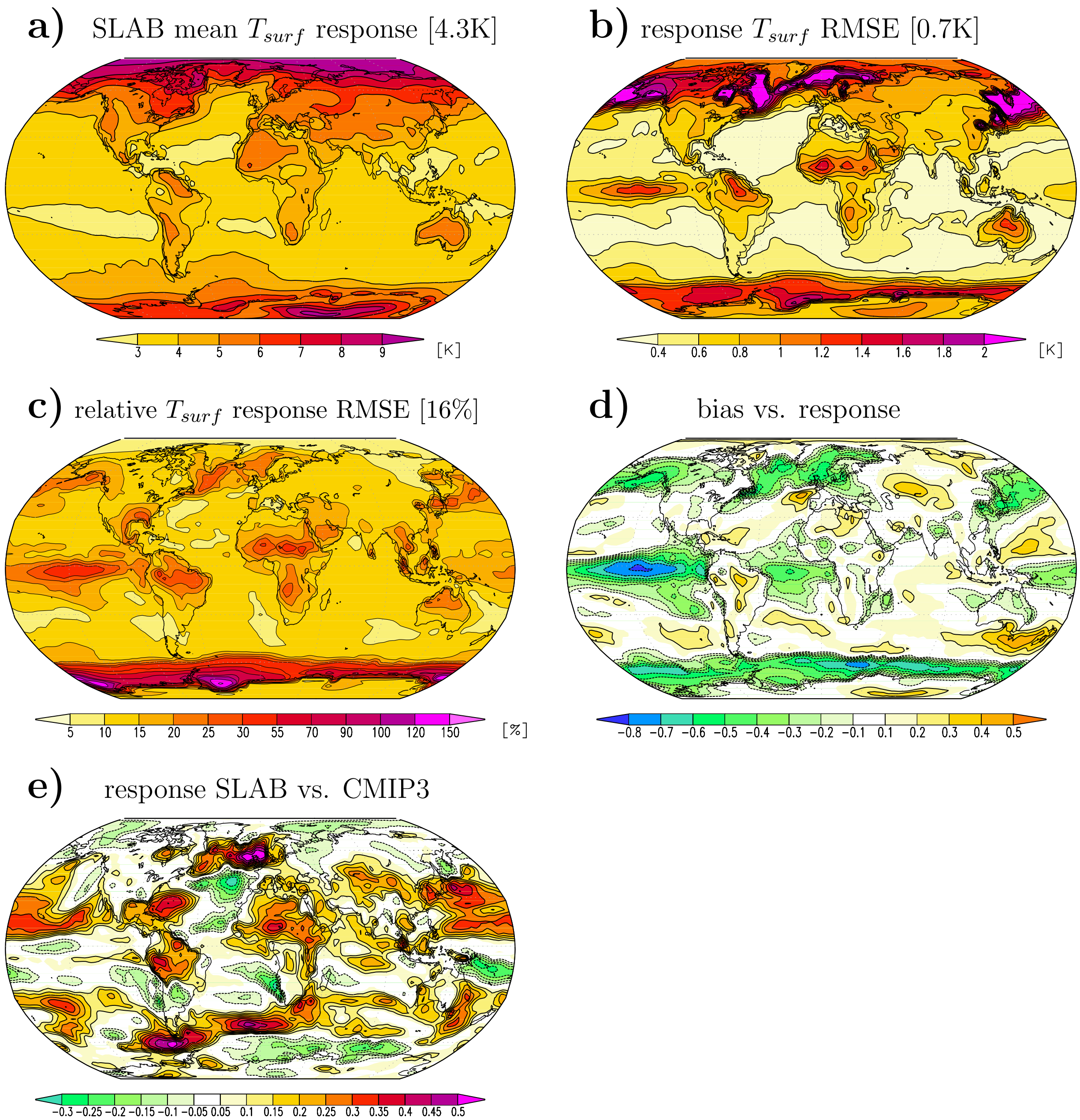

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Figure 6

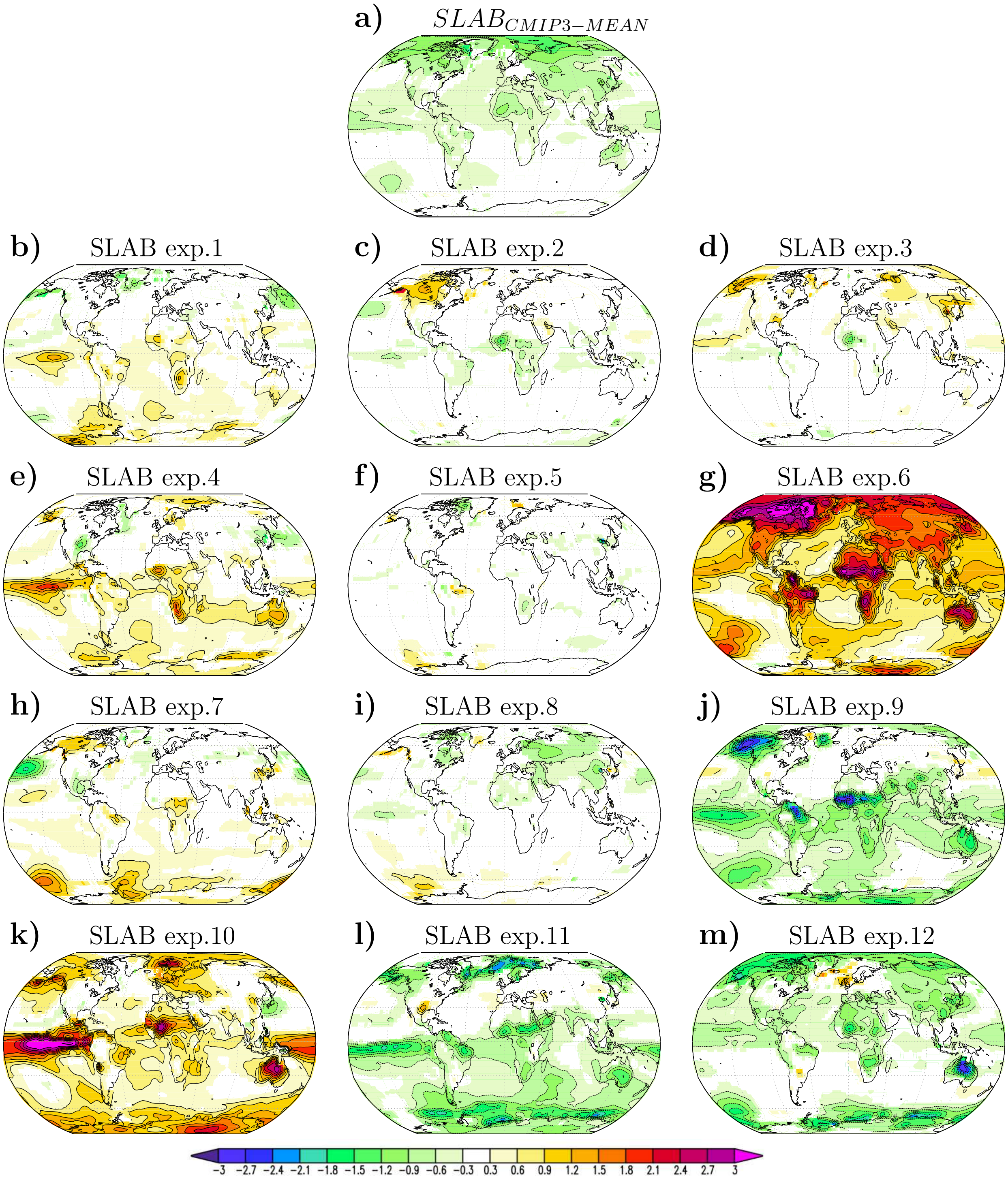

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Figure 6 part 2
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Figure 6 continued

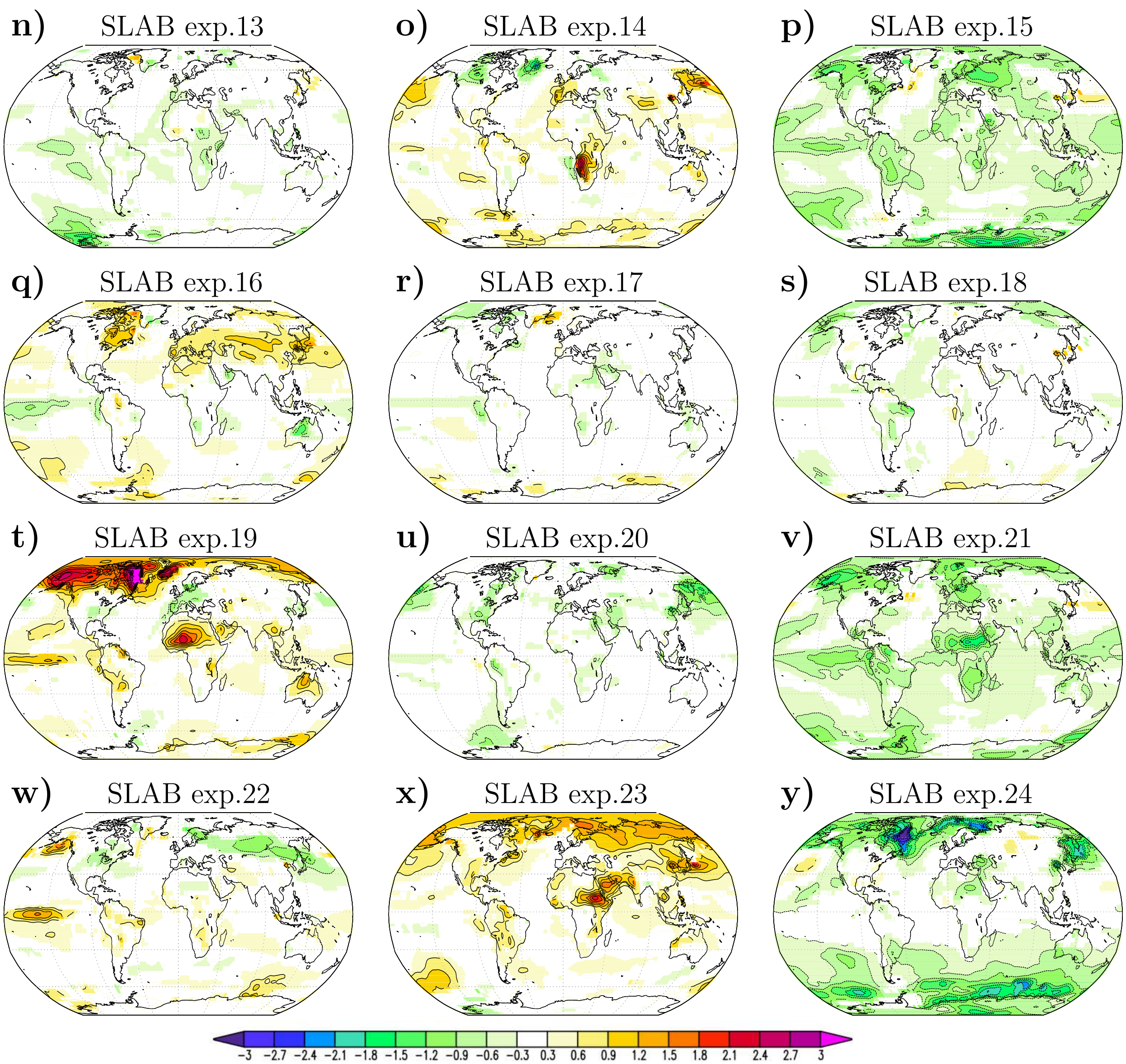

Figure 6: Continued.

Figure 7
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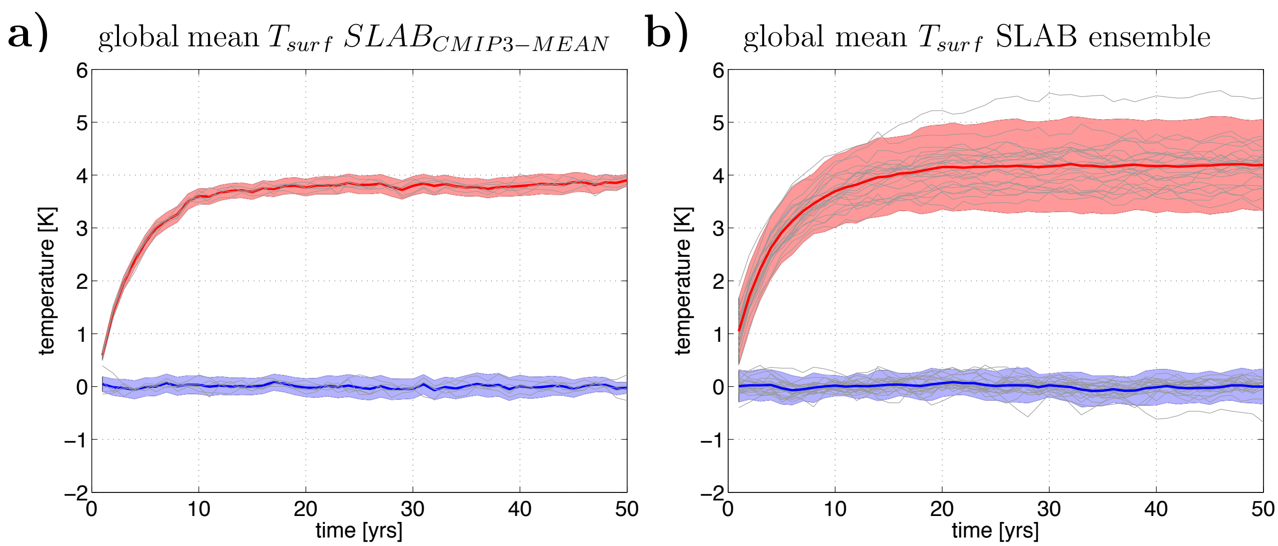
Figure 7



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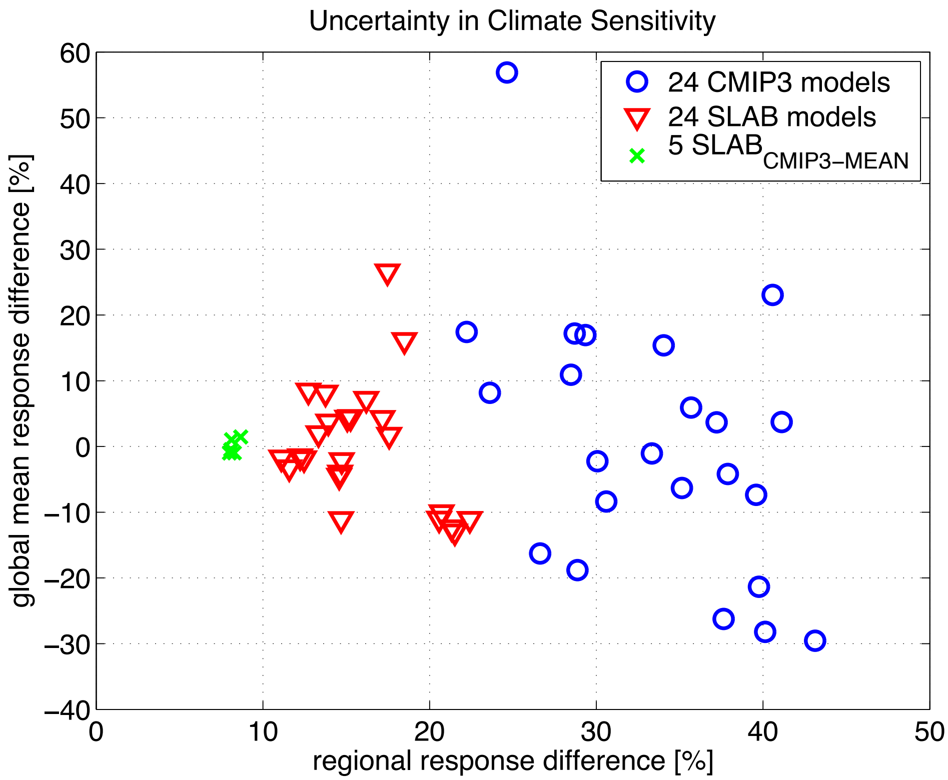

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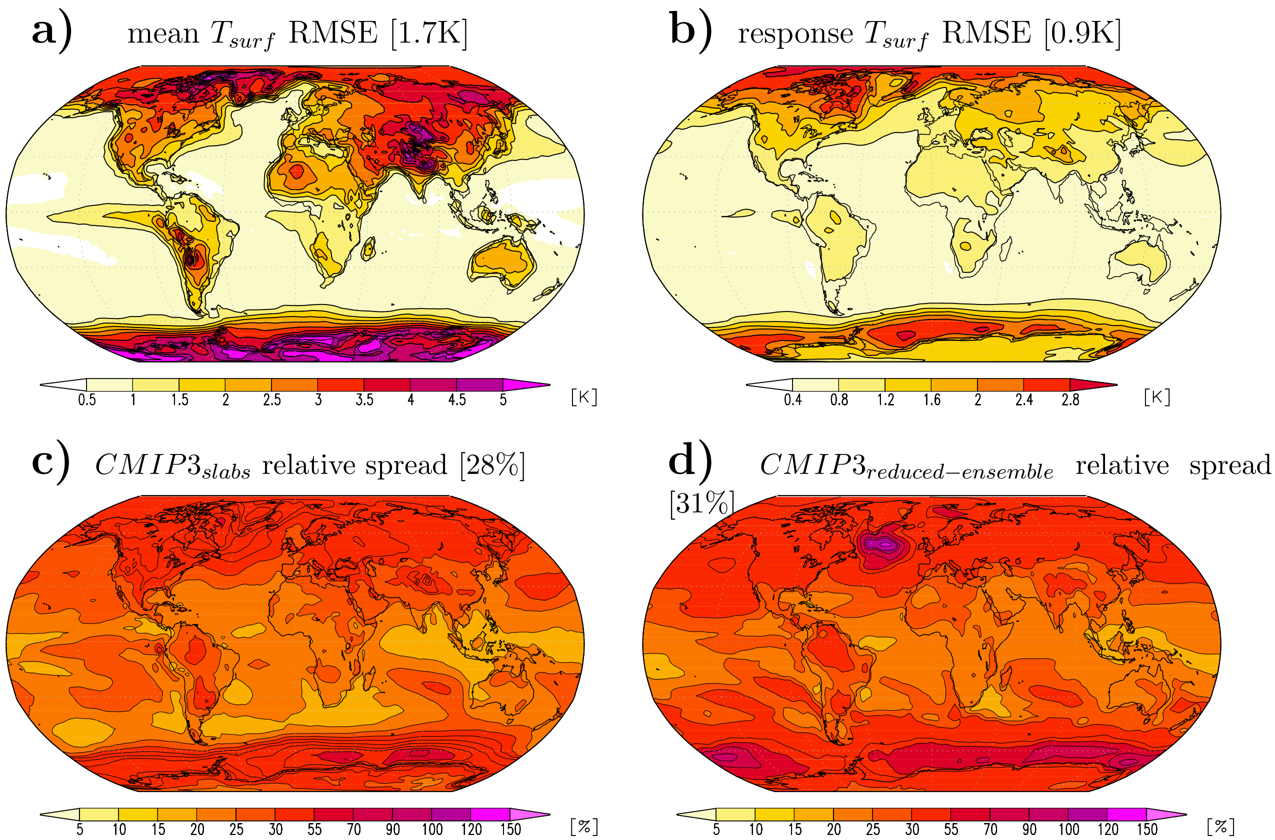

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