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A simple model perturbed physics study of the simulated climate sensitivity uncertainty and its relation to control climate biases

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Abstract In this study the relationship between climate model biases in the control climate and the simulated climate sensitivity are discussed on the basis of perturbed physics ensemble simulations with a globally resolved energy balance (GREB) model. It is illustrated that the uncertainties in the simulated climate sensitivity (estimated by the transient response to CO_2 forcing scenarios in the twenty first century or idealized $2 \times CO_2$ forcing experiments) can be conceptually split into two parts: a direct effect of the perturbed physics on the climate sensitivity independent of the control mean climate and an indirect effect of the perturbed physics by changing the control mean climate, which in turn changes the climate sensitivity, as the climate sensitivity itself is depending on the control climate. Biases in the control climate are negatively correlated with the climate sensitivity (colder climates have larger sensitivities), if no physics are perturbed. Perturbed physics that lead to warmer control climate, would in average also lead to larger climate sensitivities, if the control climate is held at the observed reference climate by flux corrections. Thus the effects of control biases and perturbed physics are opposing each other and are partially cancelling each other out. In the GREB model the biases in the control climate are the more important effect for the regional climate sensitivity uncertainties, but for the global mean climate sensitivity both, the biases in the control climate and the perturbed physics, are equally important.

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1 Introduction

The Intergovernmental Panel on Climate Change (IPCC) projections of future anthropogenic climate change are based on coarse resolution coupled general circulation models (CGCMs) from the coupled model intercomparison project (CMIP). The models of CMIP are different in their structures and physical parameterizations and have shown significant disagreement and uncertainties in their performance (e.g. Stott and Kettleborough 2002; Reichler and Kim 2008; Gleckler et al. 2008; Hawkins and Sutton 2009; Shiogama et al. 2012). The uncertainties are for the largest part caused by errors in the model formulations (Cess et al. 1990; Bony et al. 2006; Murphy et al. 2004; Meehl et al. 2007, Reichler and Kim 2008; Hawkins and Sutton 2009). A number of studies have used the perturbed physics ensemble (PPE) approach to estimate the uncertainties in the model predictions resulting from model uncertainties (e.g. Murphy et al. 2004; Stainforth et al. 2005; Collins et al. 2006; Sanderson et al. 2008a, b). The focus in these studies is mostly on quantifying which processes cause the largest uncertainty in the global mean climate sensitivity, as typically estimated by the transient response to CO_2 forcing scenarios in the twentyfirst century or idealized $2 \times CO_2$ forcing experiments.

It is interesting to note in this context, that very little attention has been given to the fact that uncertainties in the model processes will not only cause uncertainties in the climate sensitivity (for the global mean as well as on regional scales), but will also cause the models control climate

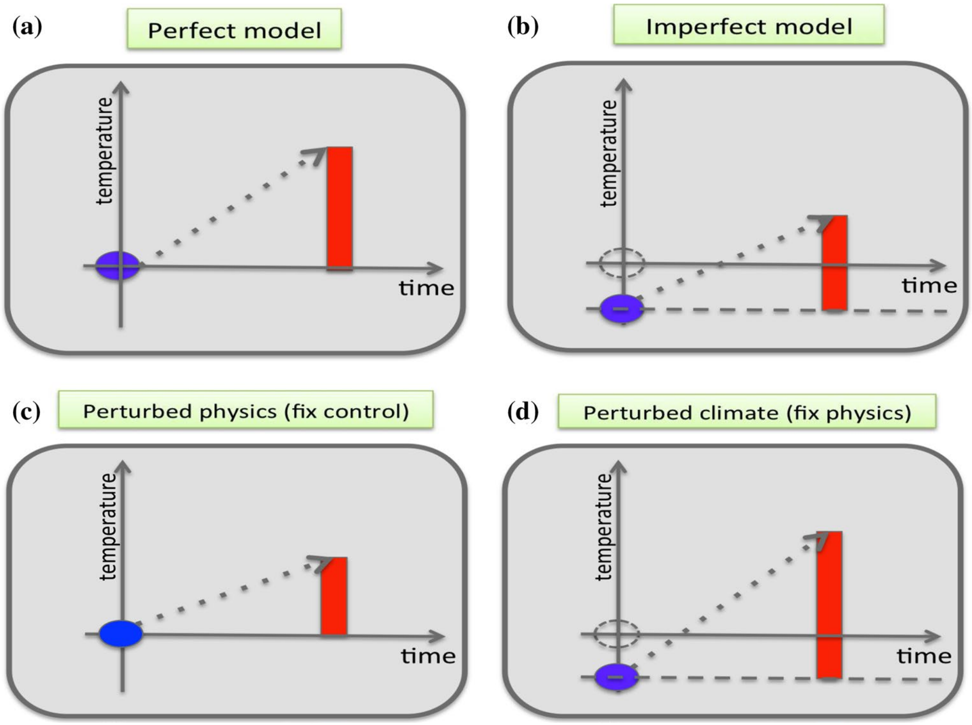


Fig. 1 Sketch illustrating the climate sensitivity in the real world (**a**) and the simulated climate sensitivity of imperfect models due to mean state biases (**b**, **d**) and due to perturbed physics (**b**, **c**)

mean state to be different from that observed and different between different models. Indeed many PPE simulations force the climate mean state to be close to the observed by flux correcting the mean sea surface temperature (SST) (e.g. Stainforth et al. 2005; Collins et al. 2006; Yokohata et al. 2010; Sanderson 2011), but therefore do not allow an estimate of how the perturbed physics may affect the mean control climate. The effect, that model uncertainties or perturbed physics may have for the predicted climate sensitivity, can be thought of as having two components: one is the change in the physics that leads to changes in the climate sensitivity from a given control climate mean state and the second is the change in the control climate mean state, which leads to a change in the climate sensitivity, as the climate response to external forcing itself is mean state dependent (Manabe and Bryan 1985; Brierley et al. 2009; Colman and McAvaney 2009; Jonko et al. 2012; Dommenget 2012 hereafter as D12; Caballero and Huber 2013; Hodson et al. 2013).

Figure 1 illustrates the concept in a sketch: In a perfect model the climate is at a the observed (correct) mean state (blue circle) from which it will warm over time by a certain amount due to the external forcing (red bar). An imperfect model (Fig. 1b) will have a control mean state climate that is different from that observed (the perfect model) due to imperfect simulation of the climate physics (blue circle). From this different mean state it will warm by a different amount than the real world (perfect model) would for the same external forcing (red bar). The difference in the climate sensitivity here results from two errors: first, the imperfect simulation of the physical processes in the model would let the model respond with a different climate sensitivity than the perfect model if the model would be started from the same mean state (equilibrium) control climate (Fig. 1c). Second, a perfect model that would be started from the different control mean state (equilibrium) climate of the imperfect model, would again have a different amount of warming than the perfect or imperfect model would to the same external forcing (Fig. 1d), because the climate response to external forcing itself is mean state dependent.

The aim of this study is to explore how important the two components of the errors are and how they may interact to build the total model uncertainty. However, since testing these conceptual ideas with fully complex CGCM simulations is fairly difficult and expensive this study here presents a first test of concept with a much simpler and cheaper, reduced complexity model. The study will present analysis of PPE simulations using the Globally Resolved Energy Balance (GREB) model from Dommenget and Floeter (2011; hereafter as DF11). While the GREB model is quite different in its structure and physical parameterizations to typical CGCMs, it is still complex enough to give a good first order approximation of how climate mean state biases and errors in the physics may relate to each other. It is capable to simulate realistic global and in particular regional patterns of climate sensitivity. Since it is numerically very cheap it allows a first order estimation of the interactions that may motivate follow up studies to verify these findings with more realistic GCGMs.

The paper is organized as follows: In the following section we introduce the data used, the model simulations and methods for the data analysis. In the first analysis section we take a short look at some statistical characteristics of the CMIP model simulations spread in their control mean and in the response to CO_2-forcing scenarios. This is used as background information for the main part of this study, which is the analysis of the GREB model perturbed physics ensembles in Sect. 4. In Sect. 5 we take a closer look at how different mean states in the GREB model affect the climate sensitivity. The study is concluded with a summary and discussion section.

2 Data and methods

The CMIP model simulations are taken from the CMIP3 and CMIP5 databases (Meehl et al. 2007; Taylor et al. 2012). All models that have the CMIP3 A1B or CMIP5 RCP 4.5, 6.0 and 8.5 scenarios are used, see Table 1. A number of CMIP3 models have several realizations of the A1B scenario with independent initial conditions. These simulations are used to estimate the spread in the response to the A1B CO_2-forcing that is entirely due to internal variability (initial conditions and internal natural fluctuations within the simulations).

The PPE simulations for this study are performed with the GREB model from DF11. The GREB model is a three layer (atmosphere, surface and subsurface ocean) global climate model with a horizontal resolution of $3.75° \times 3.75°$, that simulates the thermal and solar radiation in the atmosphere, heat transport in the atmosphere by isotropic diffusion and advection with the mean winds, the hydrological cycle (evaporation, precipitation and water vapor transport), a simple ice/snow albedo feedback and heat uptake in the subsurface ocean. The emissivity (for the thermal radiation) of the atmospheric layer is a three-band log-function fitted to observational and model data, simulating the effects of CO_2, water vapor, clouds and residual trace gasses. The GREB model has mean winds and total cloud cover as seasonal prescribed boundary conditions. Thus the GREB model is conceptually very different from the CGCM simulations of the CMIP database as the circulation of the atmosphere and the oceans are not simulated. In equilibrium to all external boundary conditions this model does not have any internal natural variability due to weather fluctuations, as non-linear weather dynamics are not simulated in the GREB model. For a complete description of the model see DF11.

All parameters and boundary conditions of the GREB model that are uncertain are being perturbed for the following analyses. Due to the different structure of the GREB model compared to CGCMs the perturbed parameter of the GREB model may not have a matching parameter in the CGCMs. However, it will be discussed in the analysis section that the overall characteristics of the uncertainties resulting form the parameter perturbations are indeed quite similar in many aspects to those seen in CGCM simulations. As described in DF11 processes or boundary conditions can be switched off in the GREB model and be replaced by constant fluxes. This allows testing of the influence of processes on the response to external forcing by maintaining the same mean control climate with the constant fluxes replacing the mean process tendencies.

The GREB models main advantage for this study is that it is very simple, numerically cheap (one simulation year per second on a standard personal computer) and the control mean state climate can be controlled by flux corrections of the surface temperature, T_{surf}, the total atmospheric water vapor content and the subsurface ocean temperatures. A further advantage is that the GREB model has no internal natural variability. Thus all GREB model variables are in equilibrium (constant) when no boundary conditions or model parameters are changed. In turn all variations that are seen in the GREB model variables in the control mean or response to doubling of CO_2 forcing due to perturbed parameters can be directly related to the parameter changes. The GREB model also allows for very simple deconstruction of the climate system by switching off processes or boundary conditions. For details of this model see DF11.

In the following analyses we estimate the climate sensitivity (for the global mean as well as on regional scales) of models by the transient response to CO_2 forcing scenarios in the twentyfirst century or by the response to idealized $2 \times CO_2$ forcing experiments. In all CMIP simulations the response to the CO_2-forcing scenarios is defined as the difference between the periods 2079 and 2099 minus 1979 and 1999. The T_{surf} ensemble mean response pattern relative to the global mean value are very similar (pattern correlation >0.95) in the A1B and RCP scenarios. In the context of this study it therefore in all following analysis assume that the relative uncertainties in these ensembles can be directly compared.

In the GREB model simulations the response to the $2 \times CO_2$-forcing is defined as the difference between year 50 of the $2 \times CO_2$-forcing simulation minus the control mean. Again note, that the GREB model does not have internal weather variability, which is why the response to external forcing can be estimated by a single year. We use these responses to the CO_2-forcing scenarios as the estimate for climate sensitivity on regional and global mean scales.

Table 1 List of CMIP3 and CMIP5 model simulations analyzed

CMIP3		CMIP5	
Model	A1B scenario ensemble members	Model	Scenarios
BCCR-BCM 2.0	1	ACCESS 1.0	RCP: 4.5/-/8.5
CCCma 3.1 (T63)	1	ACCESS 1.3	RCP: 4.5/-/8.5
CCCma 3.1	5	BCC CSM 1.1 m	RCP: -/6.0/8.5
CNRM-CM3	1	BCC CSM 1.1	RCP: 4.5/6.0/8.5
CSIRO Mk3.0	1	BNU-ESM	RCP: 4.5/-/8.5
CSIRO Mk3.5	1	CCSM4	RCP: 4.5/6.0/8.5
GFDL CM2.0	1	CESM1-BGC	RCP: 4.5/-/8.5
GFDL CM2.1	1	CESM1-CAM5	RCP: 4.5/6.0/8.5
GISS-AOM	1	CMCC-CM	RCP: 4.5/-/8.5
GISS E–H	3	CMCC-CMS	RCP: 4.5/-/8.5
GISS E-R	5	CNRM-CM5	RCP: 4.5/-/8.5
IAP FGOALS-g1.0	3	CSIRO-Mk 3.6	RCP: 4.5/6.0/8.5
INGV ECHAM4	1	CanESM2	RCP: 4.5/-/8.5
INM CM3.0	1	FGOALS-g2	RCP: 4.5/-/8.5
IPSL CM4	1	FGOALS-s2	RCP: -/-/8.5
MIROC3.2(hires)	1	FIO-ESM	RCP: 4.5/-/8.5
MIROC3.2(medres)	3	GFDL-CM3	RCP: 4.5/6.0/8.5
MIUB ECHO-G	3	GFDL-ESM2G	RCP: 4.5/6.0/8.5
MPI ECHAM5	4	GFDL-ESM2 M	RCP: 4.5/6.0/8.5
MRI CGCM2.3.2a	5	GISS-E2-H	RCP: 4.5/6.0/8.5
NCAR CCSM3	7	GISS-E2-H-CC	RCP: 4.5/-/-
NCAR PCM 1	4	GISS-E2-R	RCP: 4.5/6.0/8.5
UKMO HadCM3	1	GISS-E2-R-CC	RCP: 4.5/-/-
UKMO HADGEM1	1	HadGEM2-AO	RCP: 4.5/6.0/8.5
		HadGEM2-CC	RCP: 4.5/-/8.5
		HadGEM2-ES	RCP: 4.5/6.0/8.5
		INM CM4	RCP: 4.5/-/8.5
		IPSL-CM5A-LR	RCP: 4.5/6.0/8.5
		IPSL-CM5A-MR	RCP: 4.5/6.0/8.5
		IPSL-CM5B-LR	RCP: 4.5/-/8.5
		MIROC-ESM-CHEM	RCP: 4.5/6.0/8.5
		MIROC-ESM	RCP: 4.5/6.0/8.5
		MIROC5	RCP: 4.5/6.0/8.5
		MPI-ESM-LR	RCP: 4.5/-/8.5
		MPI-ESM-MR	RCP: 4.5/-/8.5
		MRI-CGCM3	RCP: 4.5/6.0/8.5
		NorESM1-M	RCP: 4.5/6.0/8.5
		NorESM1-ME	RCP: 4.5/6.0/8.5

Analyses of the mean control and response spread are based on monthly mean anomalies. In the CMIP ensembles anomalies are defined relative to the ensemble mean values (12 months climatology) and in the GREB model anomalies are defined relative to the original GREB model. For the 'internal variability' (referred to later in the analysis section) ensemble of the CMIP3 A1B models with several realizations the anomalies are defined relative to the ensemble mean of each individual model.

The spread or uncertainty in the climate sensitivity for each individual simulation is quantified for the global mean by the response difference from the corresponding ensemble mean of each model normalized by the corresponding ensemble mean response (as in D12). This allows comparing different scenarios on the same scale. The uncertainty in the local response amplitude (or pattern uncertainty) is estimated (as in D12) by the normalized response pattern spread of each model relative to the normalized ensemble mean response pattern:

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

with the T_{surf} response for the climatological month, m, of the individual models, $T_i(m,x,y)$, and that of the ensemble mean, $T_{ensemble}(m,x,y)$, and their respective global means, $\hat{T}_i$ and $\hat{T}_{ensemble}$, and the area size weight, $w(x,y)$. The normalized response pattern spread of each model, σ_i, gives a measure of the relative uncertainty of the local response amplitudes, independent of the global mean response. This definition is essentially a standard deviation or a root mean squared error assuming the ensemble mean would represent the truth. This pattern spread 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 response. 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.

It is useful here to clarify the wording for climate sensitivity uncertainty, error or spread: In the GREB model ensemble we assume the unperturbed model as the truth and all deviations form it or spread in the perturbed GREB simulations are discuss as uncertainties or errors. Thus we assume a perfect model world. Again it should be noted here that the GREB model has no internal variability.

In the CMIP model ensemble the spread relative to the ensemble mean is caused by internal variability, differences in the model physics and numerics. Furthermore, it is not known how the model ensemble mean relates to the true observed climate mean or sensitivity, as the true observed values are unknown. We thus refer to the CMIP model spread simply as spread. In some cases when we can neglect internal variability or when we relate the CMIP simulation to the GREB perturbed model ensemble we refer to the CMIP spread as uncertainties or errors.

3 Control climate biases and climate sensitivity uncertainties in the CMIP5 simulations

We start the analysis part with a look at the spread in the CMIP5 model simulations T_{surf} response to CO_2 forcing and its relation to the control climate variations, which is useful background information for the following GREB model study. Figure 2 shows a few statistics for the T_{surf} control and response spread, which is an update with the CMIP5 simulations of what has also been shown in D12 for CMIP3 (Fig. 1 in D12). Similar to what was shown in D12 the CMIP model simulations control mean T_{surf} spread is largest over the continental and Polar Regions, and is in the order of 2–4 K. The spread in the T_{surf} response is similar to the control T_{surf} spread.

The T_{surf} response spread in the CMIP ensemble is about 15–40 %, but is strongly enhanced over the northern North Atlantic and in the Southern Ocean. In the CMIP5 simulations there is a weak negative correlation between the control and the response variations for most regions, suggesting that regions with colder mean T_{surf} have stronger T_{surf} responses. This is more pronounced over oceans and at higher latitudes. This result is slightly different from the CMIP3 analysis in D12. There a more positive correlation in the tropics for the CMIP3 simulations was found.

Figure 3 illustrates the spread relative to the ensemble mean in the global mean and the regional response patterns for several CMIP3 and CMIP5 ensembles (see Sect. 2 for details). The spread of four different scenarios, where each ensemble member is from a different CGCM, are compared to an estimate of the spread due to internal variability (labeled 'internal variability'). The internal variability estimate is defined based on several CMIP3 CGCMs that have simulated the A1B scenario with at least three different realizations. Each point in this ensemble marks the spread of a single run from one model relative to the ensemble mean of the same model (see Sect. 2 for details). Thus the spread in this ensemble is entirely due to different initial conditions and internal natural variability simulated in the individual scenario runs.

A number of important characteristics can be found here:

- The spread (relative to the ensemble mean response) in the global mean and in the regional pattern due to internal variability is much smaller than the spread in the CMIP3 and CMIP5 ensembles. Thus the latter is primarily caused by differences (errors) between the CGCMs.
- The spread in the CMIP5 ensembles are about as large as in the CMIP3 ensemble despite the model improvements in the more advanced CMIP5 ensembles. However, it has to be noted here that at the same time as the CMIP5 model have improved in their physical representations of the processes that are simulated in the CMIP3 models as well, they have also significantly increased in complexity by including more processes that have not been simulated in the CMIP3 models (e.g. aerosol processes). Thus it is likely that the lack of reduction on the model spread is a mixture of improvements in some processes, but also inclusion of new uncertainties from newly simulated processes.

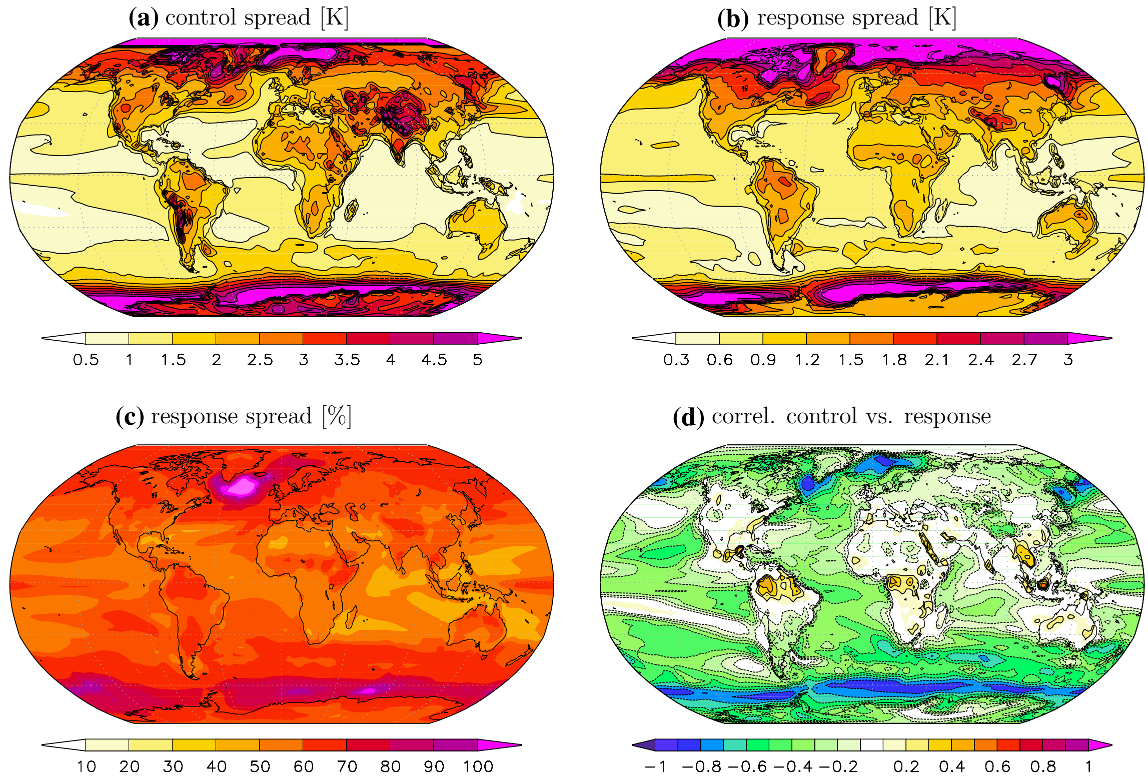


Fig. 2 **a** Spread (standard deviation) of the individual CMIP5 simulations monthly-mean T_{surf} 1970–1999 climatologies relative to the CMIP5 ensemble mean T_{surf} climatology for the same period. **b** Spread (standard deviation) of the 36 CMIP5 simulations monthly-mean T_{surf} response in the RCP8.5 scenario (mean 2070-99 minus mean 1970-99) relative to the CMIP5 ensemble monthly-mean T_{surf} response. **c** Relative response spread defined as the result in (**b**) divided by the CMIP5 ensemble mean response. **d** Correlation between the 36 monthly-mean climatologies and the responses. Anomalies for the climatologies are defined in the same way as for (**a**), and for the responses they are defined in the same way as for (**b**)

- The scenarios with stronger CO_2 forcing (compare RCP8.5 vs. RCP6 or RCP4.5) appear to have slightly smaller spread. This is to some degree expected as the smaller CO_2 forcing has a smaller signal to noise ratio, which affects the diagnostics as they are based on relative spread.

In summary, substantial response spread in the CMIP simulations are found that are caused by model differences in structure, numerics or physics and can thus be interpreted as model uncertainties or errors. They appear to have some relation to the variations in the control climate and they have not improved substantially from CMIP3 to CMIP5.

4 Perturbed physics and perturbed control climate simulations

In the following analysis we will discuss a number of PPE simulations with the GREB model, see Table 2. The PPE simulations are generated by randomly varying a number of parameters and boundary conditions of the GREB model. All model parameters and boundary conditions of the GREB model that do have some uncertainty or are model dependent are randomly varied. The strength of the variations was chosen to be within some first guess uncertainty of each parameter and boundary condition. See Table 3 for a complete list of the perturbed parameters and boundary conditions of the GREB PPE simulations.

Figure 4 shows some examples of how perturbations of a single parameter (experiments PP–SP) change the mean state control climate and how it changes the response to a doubling of CO_2. The four examples are chosen to best illustrate the concepts. A small decrease in the radiative effect of CO_2, $-\delta P_{emi}1(CO_2)$, for instance, will cool the mean climate globally (Fig. 4a), due to the reduce greenhouse effect by CO_2. Further, it will decrease the climate sensitivity to a doubling of CO_2 for most regions (Fig. 4b). However, surprisingly some regions have increased climate sensitivity (e.g. central Asia and North America). This result is at firth counter intuitive and will be discussed in more detail further below.

A small increase of the snow/ice albedo ($\delta\alpha_{ice} = +0.025$; 10 % of the original value), for instance, will cool the mean

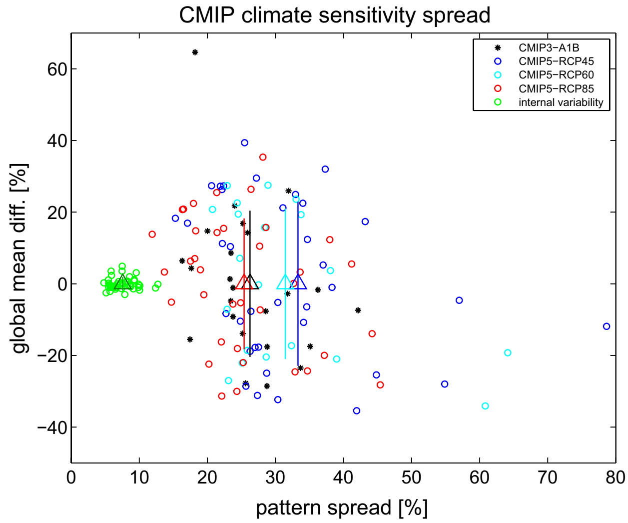


Fig. 3 Scatterplot of the CMIP3 and CMIP5 model's climate sensitivity for different scenarios and due to internal variability in the CMIP3 A1B scenario. The *x*-axis shows a measure of regional differences in the warming pattern in percentage of the corresponding ensemble mean response. It is an estimate of the mean local response amplitude deviation from the corresponding 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 triangles show the mean of the pattern spread, $\sigma_{i,}$ and global mean diff. for each ensemble. The *vertical bars* show the standard deviation of the global mean diff. distribution for each ensemble. See Sect. 2 for details

climate at higher latitudes (Fig. 4c) and will increase the climate sensitivity to a doubling of CO_2 in these latitudes (Fig. 4d), which is what you would expect from an increased snow/ice albedo. Other parameters affect the mean and the response in different ways, some have a stronger impact on the control mean, but less on the response (e.g. $+\delta r_{viwv}$ in Fig. 4e, f) and others will have a stronger global impact on both, but with different regional pattern to other parameters (e.g. $\delta\alpha_{clouds}$ Fig. 4g, h).

The effect that each of these parameters has on the climate sensitivity to a doubling of CO_2 is a combination of two effects: changes in mean state control climate (resulting from the perturbed physics) and the changes in the physical processes incorporating these parameters. To illustrate this two additional sensitivity experiments are performed: In the first experiment the parameters are perturbed as in the previous perturbed physics experiment (PP–SP), but the control mean state (on every grid point; including land, ocean and sea ice points) is held close to the observed by adjusting the Q_{flux} corrections (see Sausen et al. 1988; Schneider 1996 for the concept of flux corrections) and start the double CO_2 experiment from this observed mean state (as illustrated in Fig. 1c; referred to as PP–FC–SP). In the second experiment the parameters are not perturbed, but the Q_{flux} corrections are changed to force the GREB model into the control mean state from the PP–SP experiments and start the double CO_2 experiment from this perturbed control state (as illustrated in Fig. 1d; referred to as FP–PC–SP). Results for four different parameters for each of the three experiments and the superposition of the PP–FC–SP and FP–PC–SP are shown in Fig. 5.

A small increase of $\delta\alpha_{ice}$, for instance, does increase the climate sensitivity in higher latitudes in the PP–FC–SP experiment (Fig. 5e), because the ice-albedo feedback is increased by the larger differences in surface albedo between ice-covered and ice free regions ($\delta\alpha_{ice}$). A small increase of $\delta\alpha_{ice}$ also changes the mean climate in higher latitudes to be colder (Fig. 4c). This increases the ice-covered regions in the mid and higher latitudes in the control climate, and therefore also increases the ice-albedo feedback by being active over a larger area fraction and over a larger fraction of the seasonal cycle. In turn the climate sensitivity increases in higher latitudes in the FP–PC–SP experiment (Fig. 5f). Thus, in this example both the perturbed physics and the perturbed climate have similar impacts onto the climate sensitivity. The linear superposition of the two experiment results is quite similar to the perturbed physics experiment PP–SP that includes both effects (compare Fig. 5g, h). This is also the case for the linear superposition for the three other parameters shown.

The effect of the perturbed physics can, however, be quite different from the effect of the perturbed climate. For the $P_{emi1}(CO_2)$ and r_{viwv} parameters, for instance, the two effects are opposing each other, leading almost to a cancelation (first and third row in Fig. 5). This leads to the strange characteristics that the total effect of a perturbed parameter in the PP–SP experiments is the opposite of what would be expected from the physical process that was perturbed. The decrease in $P_{emi1}(CO_2)$, for instance, results into a decreased emissivity effect of the CO_2 concentrations in the GREB model. This should result in decreased climate sensitivity everywhere. But at some locations (e.g. central Asia and North America) the cooling in the control climate (Fig. 4a) counteract the changes in the climate sensitivity due to the process parameter changes, due to the increased positive feedbacks in the colder control climate.

In the PP–FC–SP experiments the changes in the climate sensitivity are much smoother and more directly related to what is expected from the physical parameter changes, than in the PP–SP experiments (compare first and last columns in Fig. 5). In PP–SP the changes in the climate sensitivity, which result from the combined effect of perturbed parameters and perturbed control climate, are more complex and are of smaller spatial scale. For the $\delta\alpha_{clouds}$ parameter (Fig. 5m–p) the changes in the response are almost entirely (values in Fig. 5m are slightly negative, but below the first contour level) due to the changes the mean climate.

Table 2 GREB model simulations

Model	Ensemble members	Control	$2 \times CO_2$ (years)	Comments
GREB	1	–	50	Original unperturbed model; control climate flux corrected towards observed, as illustrated in Fig. 1a
PP–SP	23	50 years	50	Perturbed physics (PP) simulation with a single parameter (SP) or boundary condition perturbed, as illustrated in Fig. 1b.
PP–FC–SP	23	–	50	As PP–SP, but the control climate is forced to be as observed by flux corrections (fix control; FC), as illustrated in Fig. 1c
FP–PC–SP	23	–	50	As GREB, but control climate flux corrected towards the control of PP–SP [fixed physics (FP) and perturbed climate (PC)], as illustrated in Fig. 1d
PP	500	50 years	50	As PP–SP, but with all 23 parameters and boundary conditions randomly perturbed for each member.
PP–FC	500	–	50	As PP, but the control climate is forced to be as observed by flux corrections.
FP–PC	500	–	50	As GREB, but control climate flux corrected towards the control of PP.
FP–PC–exp3	500	–	50	As FP–PC, but the ice-albedo and hydrological cycle processes are switched of, the water vapor climatology is constant over all regions and no heat transport into the subsurface ocean, as in DF11 exp-3.
FP–PC-exp4	500	–	50	As FP–PC-exp3, but realistic water vapor climatology.
FP–PC-exp6	500	–	50	As FP–PC-exp4, but with the ice-albedo feedback.
FP–PC-exp7	500	–	50	As FP–PC-exp6, but with the local (no water vapor transport) hydrological cycle feedback.
FP–PC-exp9	500	–	50	As FP–PC, but no heat transport into the subsurface ocean.
FP–PC-exp22	500	–	50	As FP–PC-exp4, but with the local (no water vapor transport) hydrological cycle feedback.
FP–PSST	500	–	50	As FP–PC, but only the ice-free SST is forced to be the mean control values of the PP simulations.
PP–FSST	500	50yrs	50	As PP, but the ice-free SST is forced to be the observed mean control values by flux corrections.

Experiments numbers for the FP–PC deconstruction ensembles are as in DF11, expect for exp-22, which was not mentioned in DF11

In the next step of the analysis all 26 parameters and boundary conditions are randomly varied to create a PPE, in which each member has slightly different parameters and boundary climatology values for all of the 26 parameters and boundary conditions (referred to as PP experiments). The standard deviations of the parameter uncertainties have been chosen in a way that the values appear to be still within the uncertainties that can be attributed to each parameter and that none of the parameters is dominating the models climate sensitivity uncertainties.

Table 3 lists the relative contribution of each parameter to the total climate sensitivity spread. It first of all needs to be noted that the parameter uncertainties interact in a non-linear way, so that the estimated relative contribution do not add up to 100 %. We can further note that none of the individual parameters is dominating and that the dominating parameters are mostly related to the effects of clouds, water vapor and small-scale turbulent processes. Thus it gives a fairly complex interaction of many uncertain parameters. This is in principle similar to those processes that cause most of the spread in CGCM simulations, but the parameters and processes of the GREB model cannot be directly compared to those of the CGCM due to the very different structure of the GREB model. It needs to be noted here again that the parameters of the GREB model in most cases do not have counterparts in the GGCMs. Uncertainties related to cloud feedbacks are entirely missing here. Nevertheless, the parameters related to cloud do have a strong impact on mean climate and on the response uncertainty, as also discussed and shown in Figs. 4 and 5.

In analog to the three sensitivity experiments with the single parameter changes, we perform three PPE simulations: perturbed physics (PP), perturbed physics with fixed control climate (PP–FC) and fixed physics with only perturbed control climates (FP–PC), see Table 2. To get a first impression Fig. 6 shows the change in the T_{surf} response to a doubling of CO_2 concentrations for six members of the 500 members of the PPE ensembles. A quantitative discussion of the whole ensemble set will be given further below. The six members illustrate similar characteristics as the four examples of the single parameter changes:

- The total response changes in the perturbed physics (PP) experiments are approximately a linear superposition of the perturbed PP–FC and FP–PC simulations (compare third and last columns in Fig. 6).
- Some random parameter changes lead to significant control climate changes that lead to changes in the response (FP–PC), whereas the PP–FC experiments lead to very little changes in the response (e.g. examples 1, 3 and 5 in Fig. 6).
- In many cases the changes in the response in the PP–FC experiments have the opposite sign of those of the FP–PC experiments (e.g. examples 2, 4 and 6 in Fig. 6).

Table 3 List of perturbed parameters and boundary conditions

Name	r^2 (Response) [%]	Comments
pe_1	7	CO_2 effect on emissivity; Eq. (5) in DF11
pe_2	9	H_2O effect on emissivity; Eq. (5) in DF11
pe_3	0.5	Residual emissivity; Eq. (5) in DF11
pe_4	2	Strength of overlap band; Eq. (5) in DF11
pe_5	1	Strength of CO_2 band; Eq. (5) in DF11
pe_6	4	Strength of H_2O band; Eq. (5) in DF11
pe_7	1	emissivity zero off set; Eq. [5] in DF11
pe_8	2	Influence of cloud cover on emissivity; Eq. (5) in DF11
pe_9	5	Influence of cloud cover on emissivity; Eq. (5) in DF11
pe_{10}	4	Influence of cloud cover on emissivity; Eq. (5) in DF11
r_{precip}	6	Precipitation ratio; Eq. (11) in DF11
r_{qviwv}	5	Regression between surface humidity and total air column water vapor; Eq. (8) in DF11
c_{atmos}	5	Atmos. Coupling to surface; Eq. (13) in DF11
α_{clouds}	4	cloud albedo; Eq. (2) in DF11
$\delta\alpha_{ice}$	2	Ice/snow albedo; from Fig. 3a in DF11
κ	1	Isotropic diffusion coefficient; Eq. (12) in DF11
C_w	0.5	Transfer coefficient for latent cooling by evaporation; Eq. (7) in DF11
$T_{sea\text{-}ice1}$, $T_{sea\text{-}ice2}$	0.3	T_{surf} range for the ice albedo feedback over oceans; from Fig. 3a in DF11
$T_{land\text{-}ice1}$, $T_{land\text{-}ice2}$	0.2	T_{surf} range for the ice albedo feedback over land; from Fig. 3a in DF11
Wind climatology	0.8	Variations in the wind climatology are based on the leading empirical orthogonal function of global monthly wind anomalies.
MLD climatology	0.4	Variations in the MLD climatology are based on the leading empirical orthogonal function of a spatial red noise process (Dommenget al. 2007) for winter and summer seasons with the effective spatial number degree of freedoms, $N_{spatial} = 50$ (Bretherton et al. 1999)
Cloud climatology	0.3	Variations in the cloud climatology are based on the leading empirical orthogonal function of global monthly wind anomalies
Soil moisture climatology	0.3	Same procedure as for the MLD

Parameter names are taken from DF11 unless otherwise noted. The relative contribution of each parameter or boundary condition perturbation to the climate sensitivity variations, are estimated by the explained variance (r^2) based on the mean (over all regions) linear correlation of the parameter variations with the annual mean response variations in the PP ensemble. Note that since the parameter interact in a non-linear way, the r^2 values do not add up to a 100 %

However, the regional details of the two experiments appear to be quite different, indicating that the effect of the perturbed parameters in PP–FC on the response is quite different from the effect that the perturbed control climate in the FP–PC has on the response.

- The changes in the response are stronger in the FP–PC experiments than in the PP–FC experiments.

Some important statistical characteristics of the PP simulations can be quantified and compared against the CMIP model simulations (Fig. 2), see Fig. 7. In all four statistical parameters for the control and response spreads we see a fairly good agreement between the global pattern in the CMIP and in the GREB PP simulations. In both ensembles larger uncertainties in the control and response are seen over land and higher latitudes (ice covered regions). The correlation between control and response variation are in both ensembles slightly negative.

However, we also find some differences in the two ensembles. In the GREB PP simulations the overall control mean surface temperature spread is somewhat larger, compared to the CMIP5 simulation and is also stronger over continental regions. The GREB PP control spread is larger over oceans and much weaker over Polar Regions, and the GREB PP response spread is weaker over most oceanic regions and more strongly focused on sea ice covered regions. The GREB PP ensemble correlation between control climate and response variations (Fig. 7d) is stronger over land and weaker in the higher latitudes than in the CMIP5 ensemble. In summary, the statistical characteristics of the control climate and response variations in the GREB PP ensemble are similar to those of the CMIP5 ensemble, but some characteristic differences do exist.

Figure 8 illustrates how the three different GREB PPE ensembles relate to each other and how the perturbed physics and perturbed climates contribute to the total changes in

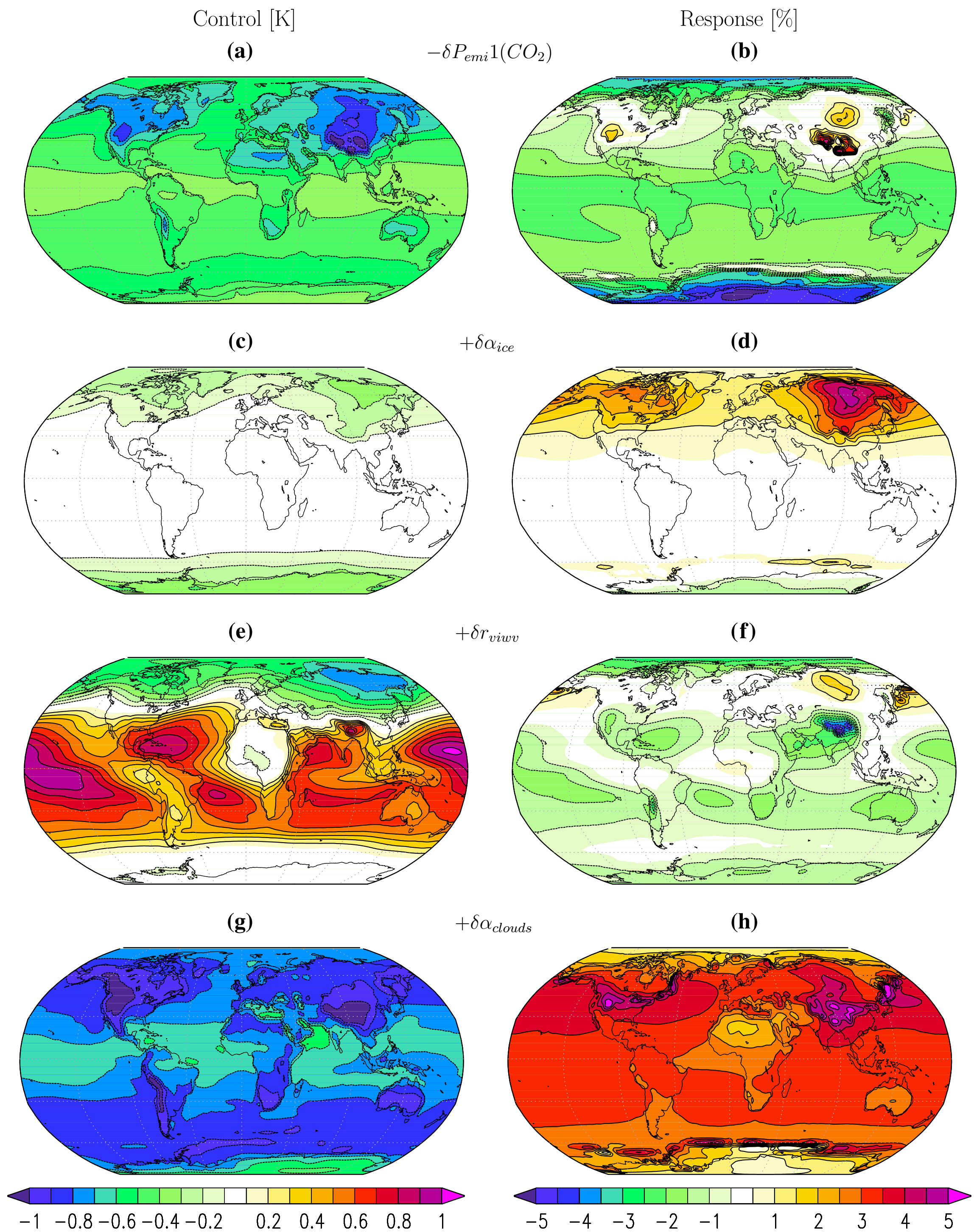


Fig. 4 *Left Column* Changes in the control mean T_{surf} due to changes in four different parameters in the PP–SP simulations. Values are in Kelvin. *Right column* Changes in the T_{surf} response relative to the GREB models unperturbed T_{surf} response due to changes in four different parameters in the PP–SP simulations. Values are in % of the GREB models unperturbed T_{surf} response. **a**, **b** for $-\delta P_{emi}1(CO_2)$, **c**, **d** for$\delta\alpha_{ice}$, **e**, **f** for $+\delta r_{viwv}$ and **g**, **h** for $\delta\alpha_{clouds}$

the response. The local response changes in the PP simulations are nearly perfectly correlated to the linear superposition of the PP–FC and FP–PC simulations for nearly all regions, but not quite for the high altitudes of Tibet, Greenland and Antarctica (Fig. 8f). This indicates that the GREB PP response spread can be thought of as the sum of

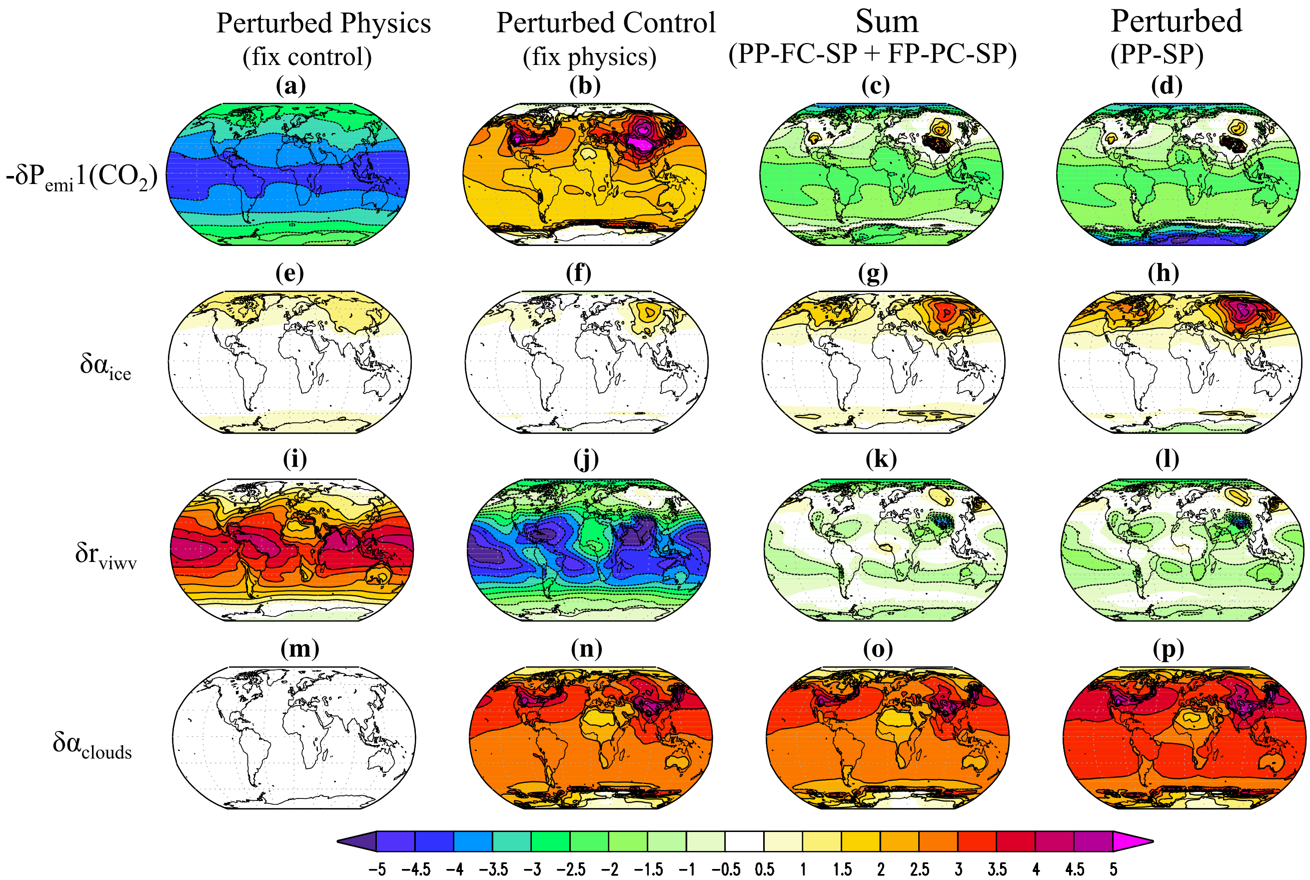


Fig. 5 Changes in the T_{surf} response relative to the GREB models unperturbed T_{surf} response due to changes in the same four parameters as in Fig. 4. *First column* perturbed physics and fixed control climate (PP–FC–SP) simulation. *Second column* fixed physics and perturbed control climate (FP–PC–SP) simulation. *Third column* the sum of the first and second column. *Last column* perturbed physics (PP–SP) simulation as in Fig. 4 right column. All values are in % of the GREB models unperturbed T_{surf} response

a perturbed physics and a perturbed climate. However, the absolute spread of the super position is larger than that of the PP simulations (compare Figs. 7c, 8e), indicating that the combined effect of the perturbed physics and a perturbed climate in the PP simulations is somewhat compensated in a non-linear way.

The FP–PC simulations have a larger response spread and are more strongly correlated with the PP simulations (Fig. 8c, d) than the PP–FC simulations (Fig. 8a, b) for most regions. This suggests that the control climate spread has a bigger influence on the response in the PP simulations than the physics perturbations themselves. Further, it is found that the response changes in the PP–FC and FP–PC simulations are negatively correlated for most regions (Fig. 8g). Thus, the effects of the perturbed physics and the perturbed climate are counter acting each other in the GREB PP simulations.

The regional uncertainties (spread) of the GREB PP simulations are larger than the global mean uncertainties (spread) (Fig. 9a), which is similar to the CMIP ensembles (Fig. 3). The GREB PP–FC simulations have strongly reduced regional spread compared to the PP simulations, but increased global mean spread. The GREB FP–PC simulations also have enhanced spread for the global mean response, but nearly no change in the regional response spread. Thus, a flux corrected mean control climate strongly reduces the regional climate sensitivity spread in the GREB PPE simulations. It can be noted in both, the FP–PC and PP–FC ensembles, that simulations with larger deviations in the global mean response also tend to have larger deviations from the ensemble mean response pattern (bimodal signatures in Fig. 9a). Thus simulations that are very different in their global mean climate sensitivity tend to have a response pattern that is different from the original response.

In the above results there is a clear distinction between the global mean and the regional response pattern sensitivity to perturbed physics and control climates. The direct perturbed physics effect is strongly counter acting the perturbed control climate effect on the global mean response, but much less so on the regional response pattern. Indeed the anti-correlation between the two effects (Fig. 8g) is

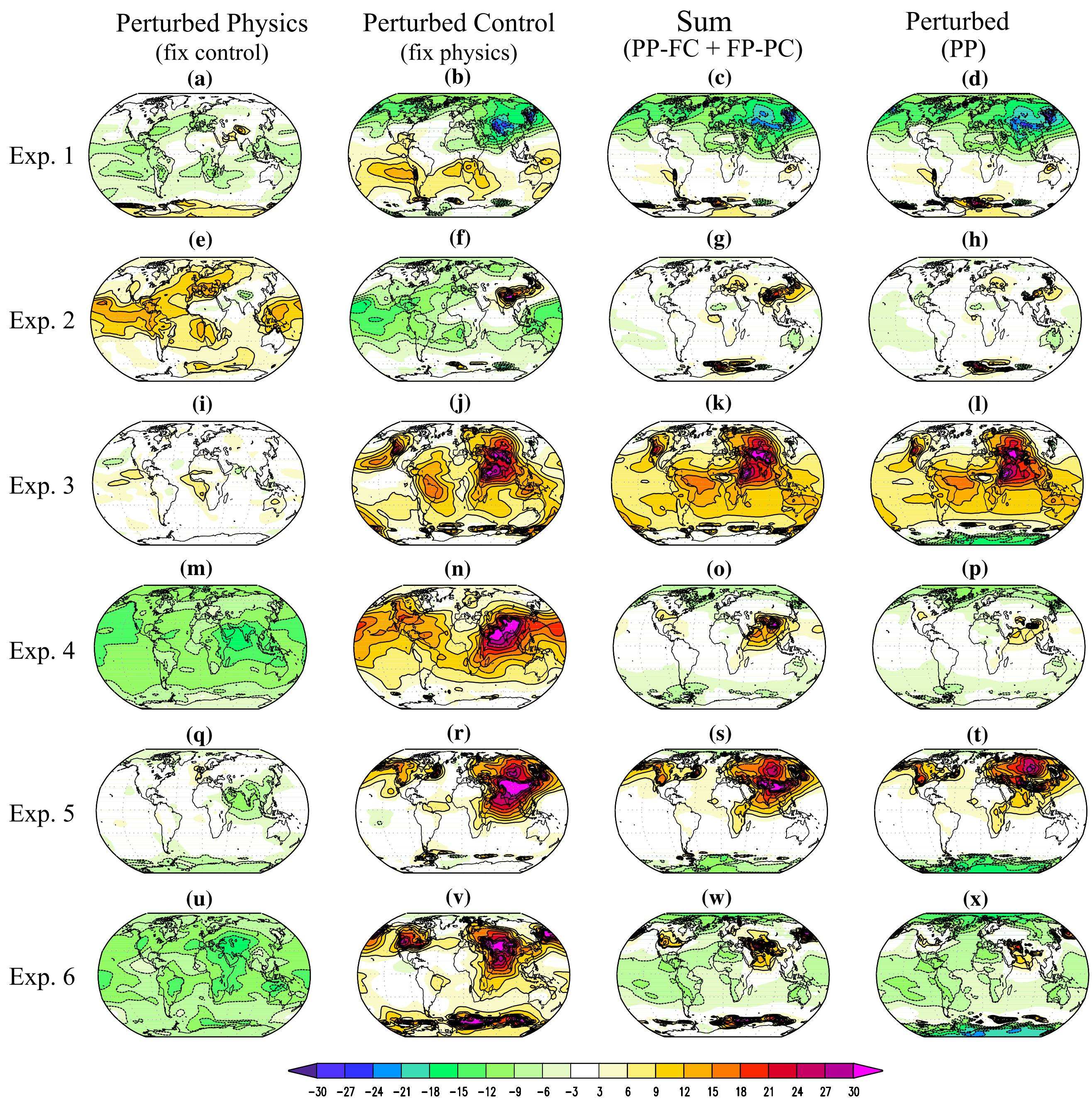


Fig. 6 Changes in the T_{surf} response relative to the GREB models unperturbed T_{surf} response as in Fig. 5, but for 6 examples from the PPE ensembles. *First column* perturbed physics and fixed control (PP–FC) simulation. *Second column* fixed physics and perturbed control (FP–PC) simulation. *Third column* the sum of the first and second column. *Last column* perturbed physics (PP) simulation. All values are in % of the GREB models unperturbed T_{surf} response

mostly due to anti-correlation in the global means (correlation of −0.85). The correlation in the response variations is only −0.4 if the global mean warmings are subtracted (as in the definition of the response pattern spread, σ_i; see Sect. 2). Thus, the small regional differences in the direct perturbed physics effect and the perturbed control climate effect cause the response pattern spread.

Next, a closer look is taken at uncertainties (spread) resulting from the SST, as these have been discussed in previous studies. The ECHAM5-SLAB ensemble of D12 illustrated that the spread in the climate sensitivity caused by the spread in the control mean SST is about half the spread in the climate sensitivity of the CMIP ensemble. The GREB PPE simulations can be used to mimic this approach

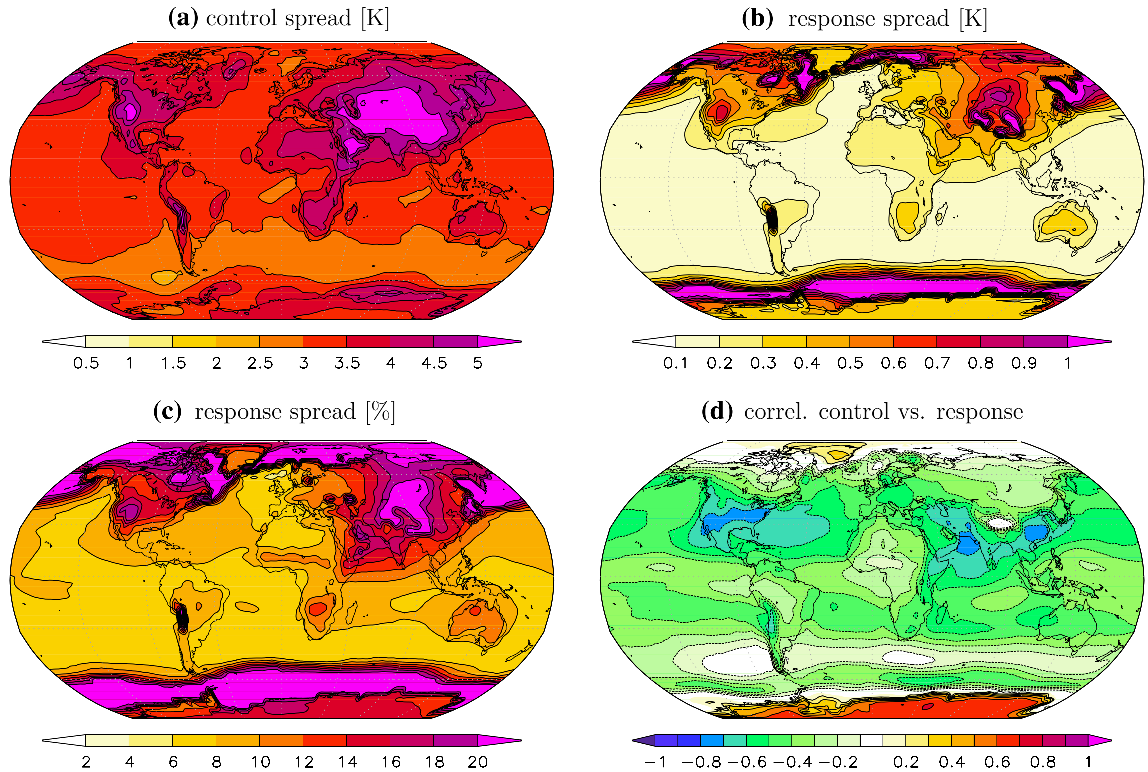


Fig. 7 Statistics as in Fig. 2, but for of the GREB PP ensemble. **a** Spread (standard deviation) of the monthly-mean T_{surf} climatologies of the PP ensemble relative to the original GREB simulation. **b** Spread (standard deviation) of the PP ensemble monthly-mean T_{surf} response in the 2 × CO_2-forcing relative to the original GREB monthly-mean T_{surf} response. **c** Relative response spread defined as the result in (**b**) divided by the original GREB response. **d** Correlation between the PP ensemble monthly-mean climatologies and the responses. Anomalies for the climatologies are defined in the same way as for (**a**), and for the responses they are defined in the same way as for (**b**). *Note* that the *colorbars* in (**b**) and (**c**) are different from Fig. 2 (**b**, **c**)

by just perturbing the control SST as it was perturbed in the PP simulations, but again keeping the parameters fixed to the original values (these simulations are referred to as FP–PSST). The GREB FP–PSST ensemble spread (red points in Fig. 9b) is about half of the GREB PP ensemble (black points in Fig. 9b). This first of all indicates that the different SST control mean state do have a substantial impact on the regional and global mean response uncertainties, which is in general agreement with D12. The results here show a somewhat stronger impact of the SST on the climate sensitivity spread than in the ECHAM5-SLAB ensemble of D12 (not shown). This may partly be due to the stronger spread in the control SST in the GREB PP ensemble than in the CMIP ensemble (see Fig. 7a, c).

In earlier CGCM model simulations the SST was often flux corrected to keep the CGCM simulation closer to the observed mean climate in the control simulation. Thus one may argue that SST flux corrected simulations should perform much better than simulations without flux corrections if the mean control climate errors do matter. To test this idea we can mimic this in the GREB PPE simulations by applying the flux correction only to ice-free SST regions and keeping the perturbed physics (these simulations are referred to as PP–FSST).

First, we can note that the GREB PP–FSST ensemble (blue points in Fig. 9b) does have a reduced regional spread relative the uncorrected PP ensemble (black points in Fig. 9b), indicating that the flux correction of the ice-free SST regions does reduce the regional response uncertainties. However, the GREB PP–FSST ensemble has much larger regional spread than the PP–FC ensemble (blue points in Fig. 9a), indicating that SST flux corrections alone are not sufficient, but that error in T_{surf} over land and ice-covered region are important too.

It needs to be noted here that the SST spread is larger in the GREB PP simulations than in the CMIP ensemble (Figs. 2a, 7a). Thus the relative rule of SST errors is overstated in the GREB model. Further, it needs to be noted that SST flux correction in CGCMs is not working as precisely as in the GREB model, leaving some significant SST biases in the mean state (e.g. Stainforth et al. 2005; Collins et al. 2006; Sanderson 2011; Dommenget et al. 2014). Considering that a perfect flux correction of much larger SST spread in the GREB PP simulations does reduce the regional

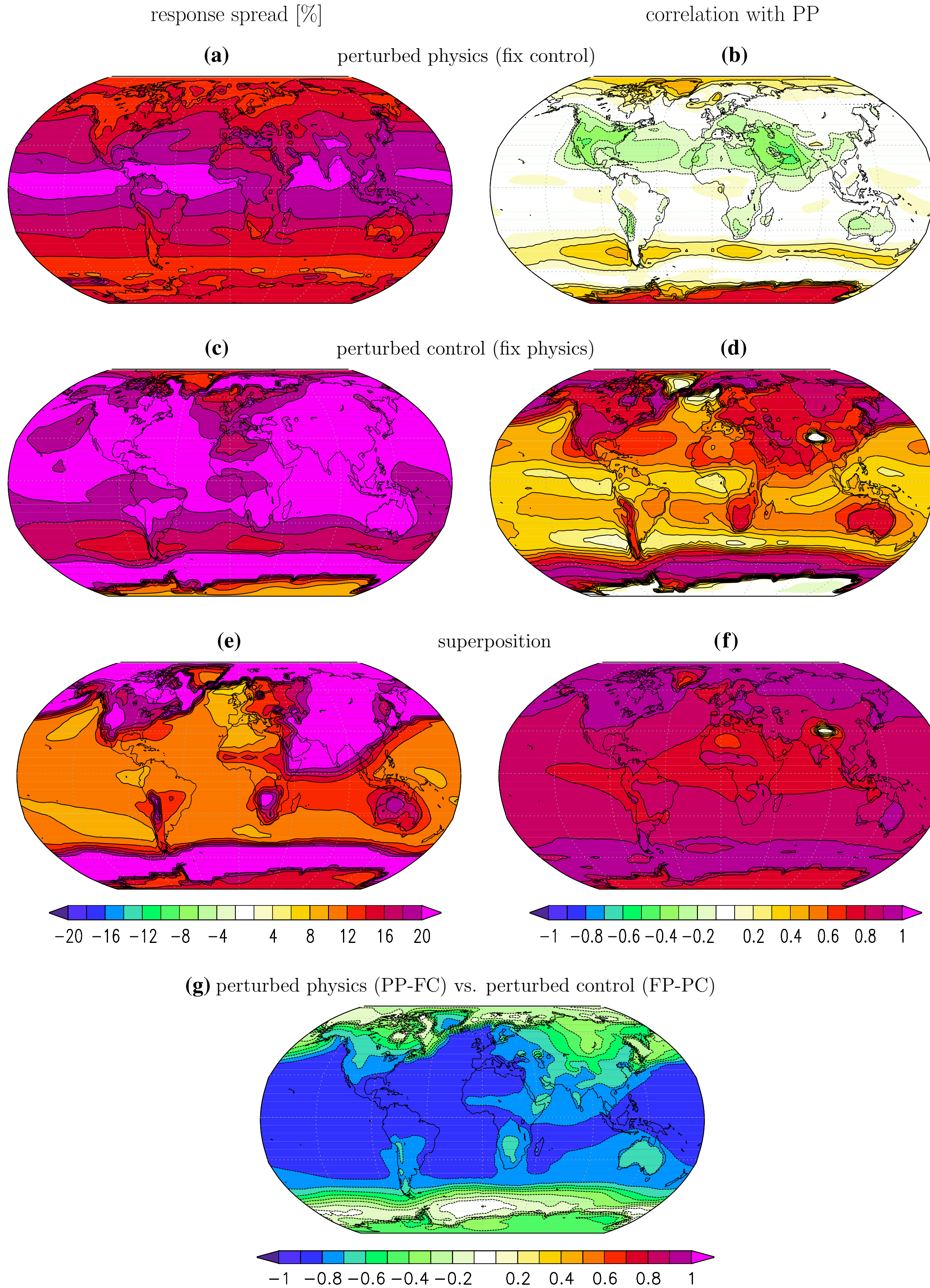


Fig. 8 *Left*: Spread (standard deviation) of the T_{surf} response as in Fig. 7c, but for **a** PP–FC, **c** FP–PC and **e** the linear superposition of PP–FC and FP–PC simulations. *Right*: The correlation between the response variations in the PP simulations and the **b** PP–FC, **d** FP–PC, and **f** the linear superposition of PP–FC and FP–PC simulations. **g** Correlation between the response variations in the PP–FC and FP–PC simulations

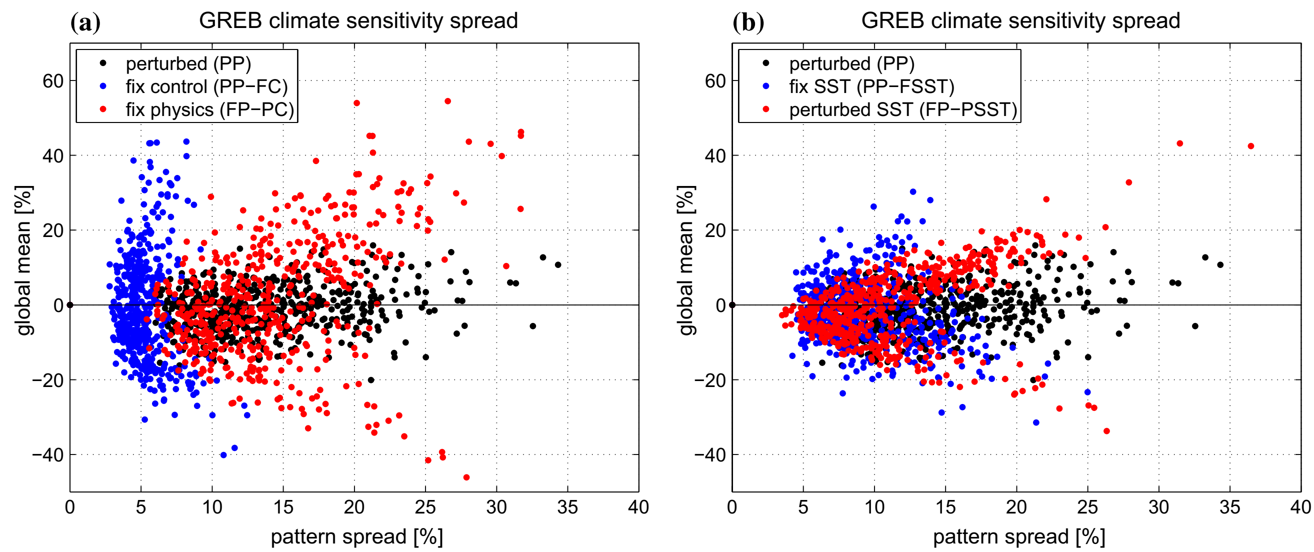


Fig. 9 Scatter plot of the climate sensitivity as in Fig. 3, but for different GREB ensemble simulations. **a** For the PP (*black dots*), FP–PC (*red dots*) and the PP–FC (*blue dots*) simulations. **b** For the PP (*black dots*), FP–PSST (*red dots*) and the PP–FSST (*blue dots*) simulations

uncertainties only by about half (blue vs. black points in Fig. 9b) and considering that SST flux corrections in the CGCMs is much less efficient, then it has to be concluded that SST flux corrected CGCMs are likely to have a similar amount of uncertainty in the regional mean control climate as the uncorrected CGCMs of CMIP simulations. We can therefore not draw any strong conclusion from SST flux corrected CGCM simulations in regards to whether or not the mean control climate errors do matter for the regional climate sensitivity uncertainties.

5 The role of the control climate for the climate sensitivity spread

In the previous section it was illustrated that the climate sensitivity spread in the GREB PP simulations is to a larger part caused by the control climate spread. It is relatively easy to understand that changes in physical parameters will change the climate sensitivity. It is, however, more complex to understand how the mean control climate spread would lead to spread in the climate sensitivity, which is the focus of this section.

Figure 10a shows the correlations of the PP control mean T_{surf} variations with the T_{surf} response variations in the PP–FC. It should be noted here again that the GRBE model does not have internal variability and the variations that we see in the control mean or response in the GREB PPE simulations (e.g. Figs. 4 or 5) are entirely a result of the perturbed physics. Subsequently the correlation values for these variations evaluate the co-variance of variations in the control mean or response due to perturbed physics.

In the PP–FC simulations we see a clear positive correlation for most regions, indicating that parameter perturbations that lead to a warmer mean state in the PP simulations also lead to larger climate sensitivity in this region in the PP–FC simulations if the simulations are started from the unperturbed control mean climates.

This can be understood if we consider that the earth without feedbacks is like the moon and has only the simple radiation balance, leading to the surface temperature. The Earth radiation balance temperature is more than 30° colder than its actual surface temperature. Thus, the net effect of all feedbacks or processes leads to more than 30° warming. This implies in turn: if the mean climate is warmer than the reference model, the net feedbacks (or the average over all possible perturbed feedbacks) are likely to be more positive, thus would lead to stronger climate sensitivity than in the reference model. Thus if a parameter perturbation leads to a warmer mean state, it is also likely to lead to a larger sensitivity to external forcings such as 2 × CO_2 forcing. However, as pointed out in Figs. 3 and 4, some process can behave contrary to this average effect (e.g. ice-albedo feedback).

The perturbed control mean state of the PP simulations is negatively correlated to the response in the FP–PC simulations (Fig. 10b). This indicates that a cooler mean state in the GREB model leads in average to a stronger response to the doubling of CO_2. This is most pronounced in the warmer and moister climates (e.g. oceans or tropics) and less so in the Polar Regions.

In the GREB PP simulations the correlation between the control mean state and the response (Fig. 7d) is also mostly negative, but much weaker than in the FP–PC simulations.

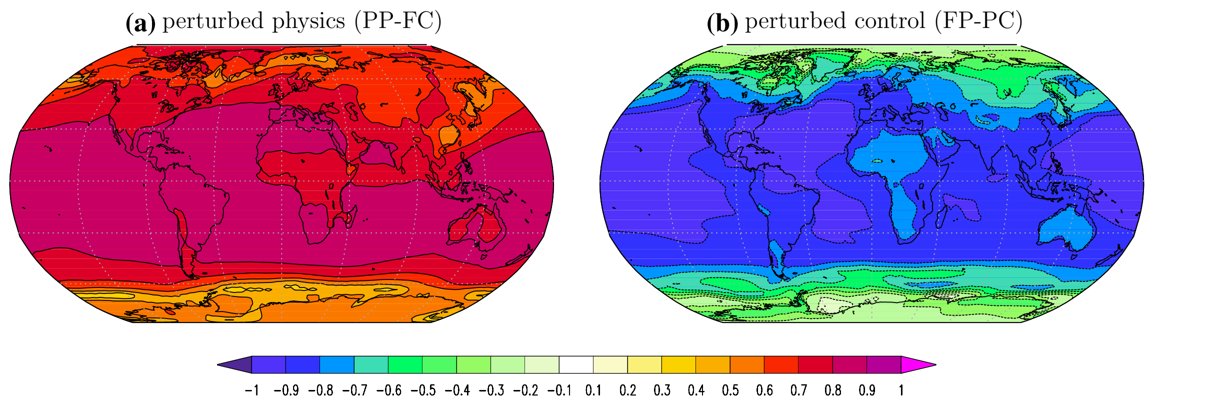


Fig. 10 **a** Correlation between the T_{surf} control variations of the PP simulation and the response variations in the PP–FC simulations. **b** Correlation between the T_{surf} control and response variations the FP–PC simulations

In the PP simulations the correlation is a result of the combined effects of perturbed parameters and the mean control climate. Since the two have opposing correlations (Fig. 10a, b), the combined effect is closer to a zero correlation. The stronger control climate effect in the GREB PP simulations is thus dominating the overall correlation. In the CMIP ensemble the correlations are even closer to zero, which may again be due to the fact that the relative importance of the control climate spread is weaker in the CMIP ensemble.

To understand how the control mean state in the GREB model affects the climate sensitivity some processes of the GREB model are switched 'off', as done in DF11. Thus the GREB FP–PC simulations are repeated with several processes switched off or some boundary conditions replaced against simplified homogenous values, see Table 2 and DF11 for details. The same experiment numbers as in DF11 are used to indicate that the same processes have been switched 'off'. These deconstructions of the GREB model simplify the interactions and allow pinning down the cause of the climate sensitivity spread in the GREB FP–PC simulations. Since some processes are switched 'off' the response to the CO_2-forcing is changing and the effect of the mean control climate is changing as well. Some of the process parameters and boundary conditions that are perturbed may not influence the results at all any more if some processes are switched off (e.g. perturbations of the ice/snow albedo do not have an effect on the response if the ice-albedo feedback if switched 'off').

Figure 11 shows the ensemble mean values in the regional and global mean response spread in the deconstructed and complete FP–PC ensemble simulations. In the simplest case without ice-albedo and water vapor feedback and without any regional difference in the atmospheric water vapor concentrations (FP–PC-exp3) the spreads in the regional and global mean are very small (note that the values are relative to the ensemble mean). It illustrates

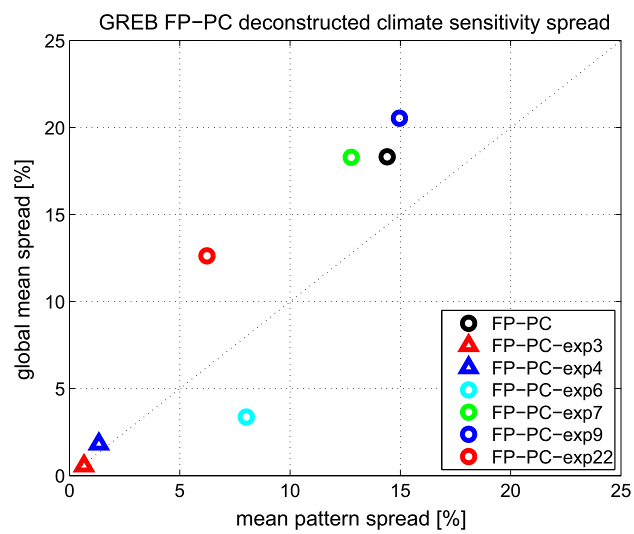


Fig. 11 Spread in the climate sensitivity for different ensemble simulations of the deconstructed GREB FP–PC simulations. The *x*-axis shows the mean of the T_{surf} response pattern spread, σ_i. The *y*-axis shows the standard deviation of the global mean T_{surf} response difference

that the differences in the control climate do not lead to any significant spread in the regional and global mean response if no feedbacks are active and no regional difference in the atmospheric water vapor concentrations exists. If we introduce the regional variation in the water vapor concentrations (FP–PC-exp4), then the spread increases in the regional and global mean, but is still much weaker than in the full GREB model. However, it will be shown in the following analysis that this initial spread due to the inhomogeneous atmospheric water vapor concentrations in the control climate is one of the main causes of the response spread in the GREB FP–PC simulations.

Introducing the two main feedbacks leads to about half of the spread for each of the two feedbacks, whereas the ice-albedo feedback (FP–PC-exp6) contributes more to the regional spread and less to the global mean spread than the water vapor feedback (FP–PC-exp22). The addition of transporting changes in the atmospheric water vapor concentration to other regions leads to some additional spread in both regional and global mean responses (compare FP–PC-exp9 and FP–PC-exp7 in Fig. 11). Finally, the introduction of the heat exchange with the subsurface oceans does effectively reduce the spread (compare FP–PC and FP–PC-exp9 in Fig. 11), although parameter perturbations in this process are introduced as well (e.g. mixed layer depth). In summary, we find that the control mean climate spread primarily leads to spread in the two main feedbacks (ice-albedo and water vapor) of the GREB model, whereas the direct response to the radiative CO_2 forcing does not have much of a spread (exp. 3 and 4).

In the left column of Fig. 12 it is shown how the responses in the deconstructed experiments correlate to the responses of the complete GREB FP–PC simulations. Most of the lower and mid latitudes of the complete GREB FP–PC response are highly correlated to the response in the FP–PC-exp4, but are anti-correlated to the FP–PC-exp3. This means that the changes in the control climate mean atmospheric water vapor concentrations are the primary source of the spread in the response in these regions. The direct response to the radiative CO_2 forcing, given the changes in the control climate mean atmospheric water vapor concentrations, are already leading to a spread in the response that is highly correlated to the complete GREB FP–PC response.

In the high latitudes and polar regions the ice-albedo feedback is the main contributor to the response of the complete GREB FP–PC simulations, as only the inclusion of the ice–albedo feedback leads to high correlations with the complete response. The water vapor feedback does also contribute in the higher latitudes, but it is relatively more important in the lower latitudes. In particular in the drier subtropical continental regions (e.g. Sahara or Australia) the correlation with the complete response is strongly increased by introducing the water vapor feedback.

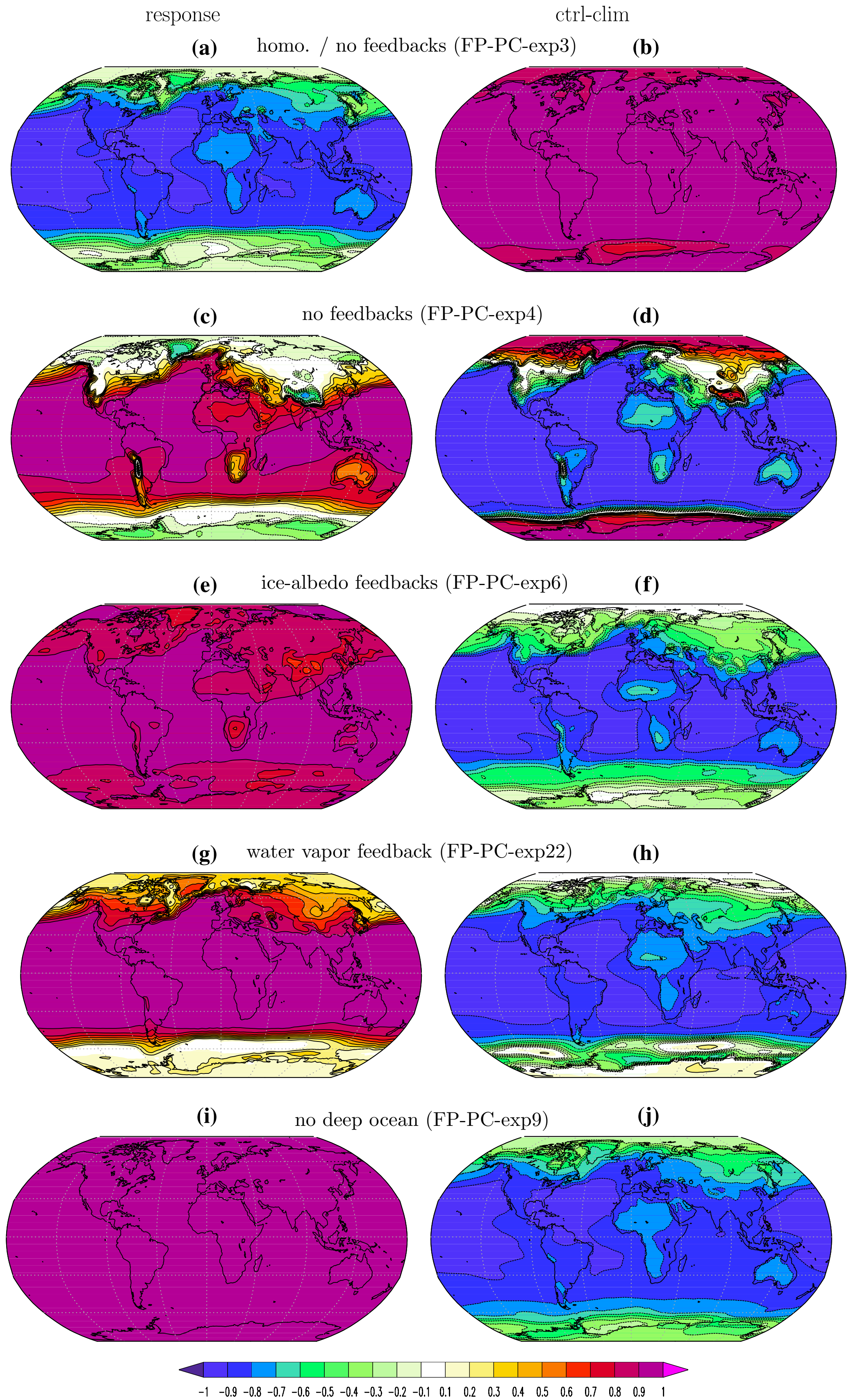
The right column of Fig. 12 shows the correlation of the response with the control climate variations, which helps to understand how the control climate influences the response of the GREB model. In the complete GREB FP–PC simulations the response in the lower and mid latitudes is strongly anti-correlated to the control climate (Fig. 10b). This anti-correlation is already present in the experiment without any feedbacks and with regional differences in the atmospheric water vapor concentration (Fig. 12d) and then becomes closer to the complete GREB FP–PC simulations with including further feedbacks and processes (Fig. 12f, h, j). The regional differences in the water vapor concentration affect the emissivity function of the GREB model (see DF11) by changing the overall emissivity of the atmosphere and by changing the sensitivity of the emissivity function to the CO_2 concentrations due to the overlap radiation band. For most lower and mid latitude regions the later effect dominates, which makes the climate more sensitive to CO_2 forcing if the water vapor concentration is smaller. Smaller water vapor concentrations are usually directly related to colder temperatures, thus we find a negative correlation between the mean climate and the response in the GREB FP–PC simulations. In higher latitudes and Polar Regions the overall emissivity effect dominates, which reduces the strength of the main negative feedback (thermal radiation) if the water vapor levels increase. Thus, warmer mean climates in these regions have a stronger response.

The water vapor and, most importantly, the ice-albedo feedback increase the negative correlation between the control and response. Colder climates make the ice-albedo feedback more efficient in most higher and mid latitudes, because the climate is more within the temperature range of the ice-albedo feedback (see DF11). Colder and drier climates are also more sensitive to increased levels of water vapor by atmospheric transport due to the water vapor feedback.

In summary, we find that the control climate variations change the regional control water vapor concentrations and thereby change the radiative effect of the CO_2 and the overall emissivity. The different mean temperatures at higher latitudes also change the ice-albedo feedback. Finally, the water vapor feedback is also altered by the mean water vapor concentrations.

6 Summary and discussion

In this study the relationship between the control mean climate biases and the climate sensitivity uncertainty (spread), both resulting from errors in the model physics, was analyzed on the basis of PPE simulations with the simple GREB model. By randomly perturbing 26 model parameters and boundary conditions of the GREB model, uncertainties or errors in the model physics were mimicked to explore how these affect the control mean climate and the model response to a $2 \times CO_2$-forcing. The perturbed physics cause the GREB model to drift from its original (observed) control mean state into a different control mean climate. From these different control mean climates the model response to a $2 \times CO_2$-forcing is estimated. Thus, the perturbed physics of the GREB model simulations lead to two errors: errors in the model physics and errors in the model mean control climate. In order to separate the two effects from each other, a number of sensitivity studies were performed, in which only one of the two errors exists. This was done by using flux corrections on T_{surf} and total


response
ctrl-clim
(a)
homo. / no feedbacks (FP-PC-exp3)
(b)
(c)
no feedbacks (FP-PC-exp4)
(d)
(e)
ice-albedo feedbacks (FP-PC-exp6)
(f)
(g)
water vapor feedback (FP-PC-exp22)
(h)
(i)
no deep ocean (FP-PC-exp9)
(j)
−1 −0.9 −0.8 −0.7 −0.6 −0.5 −0.4 −0.3 −0.2 −0.1 0.1 0.2 0.3 0.4 0.5 0.6 0.7 0.8 0.9 1

◀ **Fig. 12** *Left* Correlation between the response variations of the GREB FP–PC simulations and the response variations of the deconstructed GREB FP–PC simulations. *Right* Correlation between the control variations of the GREB FP–PC simulation and the response variations of the deconstructed GREB FP–PC simulations

atmospheric water vapor content to enforce specific control mean climates.

In the GREB PPE simulations the variations in the response to 2 × CO_2-forcing (Fig. 1b) can clearly be separated into two parts: A variation in the response to 2 × CO_2-forcing resulting from the variation in the control mean climate without any perturbed physics (Fig. 1d) and a variation in the response to 2 × CO_2-forcing resulting from the perturbed physics if the control mean is held at the observed reference climate by flux corrections (Fig. 1c). The sum of the two separated effects is highly correlated with the total variations in the response to 2 × CO_2-forcing when both effects are simulated together. The variations resulting from the biases in the control mean climate are stronger and are more closely related to the total error than those resulting from the perturbed physics only.

Further it was shown that the effects are opposing each other and are partially cancelling each other out. Perturbed physics in the absence of mean climate errors (Fig. 1c) that lead to stronger response to 2 × CO_2-forcing in a region, would also lead to warmer mean climate in the same region, if the mean control climate is allowed to drift. Thus, having a positive correlation between the variations in the control and the response. In turn the control mean biases, caused by the perturbed physics (Fig. 1d), lead to a weaker warming response to 2 × CO_2-forcing in these regions, if the GREB model with unperturbed physics is forced (by flux corrections) to start from these control biases. Thus, there is a negative correlation between the variations in the control and the response. This is in particular true for the global mean response and less so for the regional pattern differences. Qualitatively similar results have been found in some CGCM studies (Manabe and Bryan 1985 and Colman and McAvaney 2009), but other studies suggest the opposite behavior (Brierley et al. 2009; Jonko et al. 2012; Caballero and Huber 2013; Meraner et al. 2013).

Thus, the total uncertainty (spread) in the climate sensitivity is only the residual effect of the two counteracting effects. The understanding of the control bias and the perturbed physics effects on the climate sensitivity is more easily achieved when the two effects are studied separately. The direct effects of perturbed physics are leading to much simpler and easier to understand climate sensitivity changes if the control mean state is forced to be unperturbed.

The biases in the control mean climate affect the climate sensitivity mostly by altering the relative importance of the two main feedbacks: the water vapor and ice-cover feedbacks. Changes in the regional distribution of atmospheric water vapor do affect the climate sensitivity in most lower latitude regions, while at higher latitudes the changes in the T_{surf} are more relevant by affecting the strength of the ice-albedo feedback.

Two particular questions with respect to errors in the mean SST have been addressed in this study: First, does the mean SST uncertainty in the GREB model yield similar results to those of D12 and second, does flux correcting the SST lead to a reduced climate sensitivity uncertainty. For the first question the results indeed are similar to D12: spread in the control mean SST does lead to substantial spread in the response, but not nearly as strong as the total response spread. The second question is related to the general approach in previous and current CGCM simulations to flux correct the SST to improve the mean state simulations and the climate change predictions. Here, it was found that flux correcting the SST does not reduce the global mean response uncertainty and only slightly reduces the response pattern uncertainty. This reflects to some part that most of the control mean state errors are not over the open oceans, but are over land and sea-ice regions, which do not improve much if just the SSTs are flux corrected.

An obvious question is to what extent can the results of these GREB model PPE simulations tell us something about the model uncertainties of the CMIP CGCM simulations. Here, two things need to be considered: how similar are the GREB model physics to those of the CGCMs and how similar are the perturbed physics of the PPE simulations to the true errors in the CGCMs. First of all, it was shown that the GREB PPE and the CMIP ensembles have a number of similarities in the statistics of their control and response variations (comparison of Figs. 2, 3, 7, 9) and most of the response spread in both, the GREB PPE and the CMIP ensembles, results from uncertainties in the clouds, atmospheric water vapor and convection parameters. This suggests that the two ensembles have indeed some similar behavior. However, there are also a number of characteristics in which the two ensembles show some disagreement: The GREB PPE simulations have larger uncertainties in the SST and the spread in the control mean climate relative to the response spread is larger than in the CMIP ensembles, suggesting a larger sensitivity to the control mean climate. It also needs to be noted that CGCMs have significant spread in the atmospheric and ocean circulation resulting from model uncertainties that are not captured in any way in the GREB model, as the GREB model is not simulating the general circulation (e.g. uncertainties in cloud cover feedbacks). In summary, one has to be cautious when directly drawing conclusions from this study for the uncertainties of CGCMs. In particular how a particular parameter or process may influence the control bias or the climate sensitivity. The focus in this study here is more on highlighting the general interaction between control biases and climate sensitivity. While these may and will be different for different parameters or processes, the general concepts discussed here are likely to hold for most parameters or processes. In the absence of evidence suggesting the opposite, it may be advisable to assume that the CGCM simulations behave in a similar way. Thus this study served as a pilot study to evaluate a characteristic in model errors that may potentially lead to substantial improvements in CGCM simulations. The only way to get more certainty about the implications of the results of this study is to repeat a similar set of experiments with full complexity CGCMs.

A number of consequences can be drawn for the CGCM simulations, assuming the results of the GREB PPE ensembles hold also for the CMIP ensembles: The regional uncertainties in the climate sensitivity will be strongly reduced in the CGCM ensemble if the control (twentieth century) mean T_{surf} is flux corrected towards the observed not just over open oceans but globally including land and sea ice regions. This approach has so far not been applied to CGCMs, as only SST has been flux corrected in CGCMs. The global mean climate sensitivity uncertainty will not be reduced by this approach. Further, the regional uncertainties in the climate sensitivity in the flux corrected CGCM simulations will be more directly related to the process uncertainties.

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