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Forcing, Feedbacks and Climate Sensitivity in a New Generation of Climate Models

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Equilibrium Climate Sensitivity (ECS), defined as the global equilibrium surface air temperature change after a doubling of atmospheric CO_2 levels, is a relevant tool for understanding and predicting future climate change[1]. Despite decades of research and model development, climate model simulations still give a wide range of values for this quantity[2]. Understanding the reason for this range helps us understand sources of uncertainty in multi-model climate projections of the 21st century[3]. Recently, a new generation of climate models, participating in the Coupled Model Intercomparison Project phase 5 (CMIP5), have been developed and will support the Fifth Assessment Report (AR5) of the Intergovernmental Panel on Climate Change (IPCC). Their climate projections will help inform policy makers on future climate change and potential mitigation strategies. Diagnosing the climate sensitivity of these models is the first step to identifying and understanding sources of uncertainty in their climate projections. Here we apply novel analysis techniques[4] to abrupt CO_2 quadrupling experiments to quantify and compare forcing and feedback processes across a subset of available CMIP5 coupled Atmosphere-Ocean climate models. We show that certain approximations underlying methods used to estimate climate sensitivity

have to be refined to account for feedback strengths that evolve over time. The range of ECS (2.1 – 4.7 K) is similar to that found in the previous generation of models, CMIP3 (2.1 – 4.4 K)[2]. Differences in the response of clouds to climate change, and the consequent 'cloud feedback' on the Earth's radiation balance, have long been identified as the largest source of this uncertainty[2,5,6], and this remains the case in CMIP5. Improved understanding of the role of clouds[7] in climate change is therefore still needed if we want to reduce uncertainties in climate model projections.

Previously, ECS has been derived by running a model to equilibrium under a doubling of CO_2. This is too computationally expensive in coupled 3D Atmosphere-Ocean-General-Circulation-Models (AOGCMs), but it can be achieved by replacing the 3D ocean component with a simple thermodynamic mixed-layer, 'slab-ocean', model. A caveat to this design is that it suppresses changes in ocean heat transport which may be important for the pattern of surface warming and atmospheric feedbacks[8]. In addition, sea-ice schemes can be quite sensitive to ocean processes that are not represented in slab-ocean models[9]. In CMIP5, slab-ocean experiments are not included in the experiment design[10]. Different techniques are therefore needed if we want to estimate and compare the ECS of the fully coupled AOGCMs participating in CMIP5.

To estimate the ECS of the CMIP5 models we use a method[4] based on a relationship governing the energy balance of the climate system: in response to a radiative perturbation F (Wm^{-2}), the climate responds such that the change in net top-of-atmosphere (TOA) radiative flux N (Wm^{-2}) is approximately linearly dependent on global-mean surface-air-temperature change ΔT (K), such that,

$$N = F - \alpha \Delta T, \tag{1}$$

where $-\alpha$ ($Wm^{-2}\ K^{-1}$) is the 'climate feedback parameter'. If F and α are constant, N is a linear function of ΔT with a slope $-\alpha$ and intercept (at $\Delta T = 0$) of F. Diagnosed this way, F represents an 'adjusted radiative forcing' (see Methods). The equilibrium temperature change, ΔT_{eqm}, can be estimated by extrapolating this heat balance to zero heat uptake, that is, $N = 0$ and $\Delta T_{eqm} = F / \alpha$. One advantage of this method is that it

can be resolved into components that provide information on the forcing and feedback processes that determine the ECS. Another is that it allows a simple estimate of the ECS without running the model to equilibrium. On the other hand, to make this estimate, we must assume that the feedbacks are time invariant, which may not be accurate (see discussion below).

We estimate F, $-\alpha$ and ECS of the 11 available CMIP5 models by applying this method to step change (abrupt) CO_2 quadrupling experiments that are core to the CMIP5 experimental design[10] (Figure 1 and Methods). These experiments are designed to understand forcing and feedback processes in the climate system, but they are also useful for constructing policy-relevant scenarios[11]. The ECS of each model (estimated as half of ΔT_{eqm}) is shown in Figure 2, depicted in order of ECS from left to right, and tabulated in Table 1. Based on the available CMIP5 model simulations, the range of ECS is 2.6 K (2.1 to 4.7 K).

There are some differences in F across models, which might be expected from differences in their treatment of radiative transfer[12] and differences across models in rapid tropospheric and land surface adjustment processes[13-15]. In the previous generation of models, differences in feedbacks contributed more to the uncertainty in ECS than forcing[6]. In the CMIP5 models, fixing α at the multi-model mean ($\alpha = 1.05$), differences in F give an ECS range of 1.5 K (2.5 to 4.0 K). Fixing F at the multi-model mean ($F = 6.90$) however, differences in α give rise to a substantially larger range of 3.2 K (2.3 to 5.5 K). That this is larger than the actual ECS range implies an anti-correlation between forcing and feedbacks across models (correlation coefficient between F and $-\alpha$ is -0.42).

We decompose the feedbacks, which are responsible for the differences in α, into longwave (LW) clear-sky, shortwave (SW) clear-sky and net (LW+SW) Cloud Radiative Effect (CRE) (see Methods). The results are presented in Figure 2 and Table 1 (note that for completeness the regression plots for all models and all components are shown in Supplementary Figures 1-6). There is good agreement across models in strongly negative (stabilizing) LW clear-sky feedback processes (range is -1.7 to -2.0 Wm^{-2} K^{-1}), which comes about principally due to the Planck response, partly offset by a positive (destabilizing) contribution due to the net effect

of the water-vapour and lapse-rate feedbacks. There is also good agreement in positive SW clear-sky feedback processes (range is 0.5 to 0.9 Wm^{-2} K^{-1}), which comes about due to the retreat of land snow and sea-ice with warming and the water-vapour feedback, all of which decrease the planetary albedo (i.e. enhance the amount of solar radiation absorbed in the climate system).

Large differences between models emerge when we look at the response of clouds. The multi-model mean CRE feedback is close to zero (Table 1). However, the models span a wide range (-0.5 to +0.7 Wm^{-2} K^{-1}), which explains most of the range in the net feedback parameter[16]. When ordered in terms of ECS (Figure 2), it is clear that differences in CRE feedbacks relate to the range in ECS, i.e. those models with a more positive CRE feedback tend to have a larger ECS. Analysis of the CRE breakdown into SW and LW components reveals that this spread mostly comes from differences in SW CRE feedback processes (Supplementary Figure 6), as found previously in older generation models[6]. It is interesting to note that MIROC5 has a relatively low ECS (2.72 K), despite having one of the largest forcings. This is due to its particularly strong negative CRE feedback (-0.51 Wm^{-2} K^{-1}). This has been attributed to increases in low clouds over the tropical oceans in this model[17]. The Cloud Feedback Model Intercomparison Project phase 2 (CFMIP2)[18] proposes a series of model experiments that will be available in the CMIP5 multi-model dataset, such as patterned +4K experiments, they will allow us to probe differences in cloud feedback processes across models in more detail.

The CMIP5 experimental design[10] includes abrupt $4xCO_2$ experiments with fixed sea-surface-temperatures (SSTs). We use these experiments to derive an alternative estimate of the adjusted radiative forcing[19,20], which we denote by F_{SST} (see Methods). Differences between F and F_{SST} in the models with available data are generally small (Figure 2) (correlation coefficient between F and F_{SST} is 0.87). Exact agreement is not expected due to the different ways in which the methods impose $\Delta T = 0$[13,15,19-21]. For example, F_{SST} only fixes local SSTs, while land temperatures can respond, which give rise to a small global ΔT increase (Figure 2). With the regression method, on the other hand, $\Delta T = 0$, but local temperatures are unconstrained.

Some of the small differences between F and F_{SST} result from the regression method's assumption that feedbacks are linearly related to global temperature change, independent of time-scale. The regression plots (Figure 1) show, however, that in some models there are deviations from linear behaviour, suggesting some time-scale dependence of the climate feedbacks. In some models (CSIRO-Mk3-6-0, HadGEM2-ES and MRI-CGCM3, for example) F is substantially lower than F_{SST}, but if the regression lines had been based on only the first few years of data, the agreement would be better. The CMIP5 experimental design[10] does include an ensemble of 5-year 4xCO_2 experiments that could be used to obtain relatively good estimates of the effective forcing and feedback, but they will not provide information on the 'longer term' feedbacks that determine ΔT on a multi-decadal timescale. These results, however, are only beginning to be made available.

Six of the models (CSIRO-Mk3-6-0, HadGEM2-ES, MIROC-ESM, MPI-ESM-LR, MRI-CGCM3 and NorESM1-M) qualitatively demonstrate the same initial non-linearity with N in the first year falling above the regression line (Figure 1). Supplementary Figures 2-3 show that throughout the integration the clear-sky fluxes are largely linear in all of the models. At some point we might expect this to break down, at least for the surface albedo contribution to SW clear-sky feedback once snow and sea-ice disappear altogether[22]. There is some evidence of curvature in the SW clear-sky feedback processes in a few models, but the deviation from linearity is small.

Analysis of the CRE response (Supplementary Figures 4-6) reveals that the initial non-linearity is dominated by a non-linear cloud feedback. Averaging the CRE response over land and ocean regions separately reveals strong non-linearity in the SW CRE response over the ocean, not seen over land (Supplementary Figure 7). This is particularly evident in MIROC-ESM, which is strongly non-linear throughout the integration (Supplementary Figures 6-7). Consistent with a non-linear cloud response, reference [23] described a non-linear stratocumulus cloud feedback in an older generation model, which resulted from a change in the warming pattern of local SSTs in the subtropical ocean basins. Similarly, changes in the state of the deep ocean are likely to influence the pattern of surface warming and atmospheric feedbacks on a long timescale[24].

Where there are multiple timescale responses whose combined effect is not linearly related to ΔT a linear forcing-feedback framework is clearly inadequate. In these cases, the system is perhaps better characterised by an adjusted radiative forcing and a time-evolving feedback parameter, which could be defined with respect to the current climate state as the tangent to the curve[4], i.e. dN/dT. In the cases of non-linearity, estimating equilibrium climate change clearly becomes less reliable. Our F and $-\alpha$ coefficients can still be used for estimation of the ECS, but if the curve has a tendency to flatten (as suggested by Figure 1), then our estimates should be taken as an approximate lower limit[4].

Time-evolving feedbacks in CMIP5 coupled Atmosphere-Ocean climate models raise the question of whether it is still useful to focus on ECS as a means of quantifying and understanding model responses to external forcing. In the future, analysis of the adjusted radiative forcing and climate feedback parameter, including any time variation, might provide a more comprehensive characterization of the reasons for differences in model projections of future climate change, which are relevant to policy. We therefore suggest that improved understanding of climate responses on various timescales[23-35] should be a priority if we want to better constrain ECS, evaluate the limitations of the linear forcing-feedback paradigm and improve our understanding of uncertainties in multi-model climate projections.

Methods

Climate model data: Climate model data was taken from the CMIP5 multi-model data archive (http://cmip-pcmdi.llnl.gov/cmip5/index.html). We use four experiments: piControl (pre-industrial fully-coupled control, run for hundreds of years), abrupt4xCO2 (as piControl but run for 150 years with atmospheric levels of CO_2 instantaneously quadrupled), sstClim (as piControl but run for 30 years with the ocean model replaced with climatological SSTs) and sstClim4xCO2 (as sstClim but with atmospheric levels of CO_2 instantaneously quadrupled). We extracted the latest version of all model data, correct as of 16th November 2011. HadGEM2-ES has only 140 years of data currently on the CMIP5 archive for the abrupt4xCO2 experiment, but we have access to all 150 years. We extract monthly-mean data and compute global-annual-means. We calculate differences between the abrupt4xCO2 and piControl experiments by subtracting a linear fit of the corresponding control timeseries from the perturbation run, removing any model drift without adding control noise.

OLS regression: We use ordinary least square regression of global-annual-mean N against ΔT for all 150 data points to derive our best estimates of $-\alpha$ (slope) and F (intercept). Note that with this method, F includes rapid adjustments that modify the TOA radiative flux on timescales much less than a year. Thus, F is referred to as 'adjusted radiative forcing' and includes both stratospheric and tropospheric/land-surface adjustment[13-15].

ECS: We define equilibrium climate change at $N = 0$, therefore $\Delta T_{eqm} = F / \alpha$. We divide our results by 2 to apply to $2xCO_2$: $0.5 * \Delta T_{eqm} = 0.5 * (F / \alpha) = ECS$.

Uncertainties: We construct 95% (2.5-97.5%) confidence intervals on all our quantities through bootstrapping methods. We randomly sample, with replacement, 150 data points from the original dataset to create 10,000 subsets, computing the required term each time. We then sort the resulting distribution to create the 2.5-97.5% confidence interval.

Fixed-SST forcing: In the sstClim4xCO2 experiments the atmosphere and land surface is free to respond to change in CO_2 but the SSTs, and so climate feedbacks, are prevented from evolving[19,20]. This means that $\Delta T \sim 0$ (although there is some land surface warming) and $F = N$ according to Equation (1). F_{SST} is therefore calculated from a time averaged N. We calculate this as a difference from the sstClim control, to remove any common flux imbalance.

Component regressions: We decompose the net TOA radiative flux, N, into LW and SW clear-sky and net CRE components. The clear-sky diagnostics are included in the CMIP5 archive. The net CRE term is defined as the difference between the net radiative all-sky diagnostics (i.e. with clouds) and net radiative clear-sky diagnostics (i.e. no clouds). Note that changes in CRE should not be interpreted as being due to changes in cloud properties alone since the masking effects of clouds on clear-sky fluxes also contribute[26]. We then perform the same linear regression technique on these terms against ΔT.

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Author Contribution

All authors contributed to the methods and writing of the paper. TA extracted and analysed the model data.

Additional Information

The authors declare no competing financial interests. Supplementary information accompanies this paper at www.nature.com/naturegeoscience. Reprints and permissions information is available online at http://www.nature.com/reprints. Correspondence and requests for materials should be addressed to TA.

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Table 1: Forcing, feedback and climate sensitivity values. The $4xCO_2$ adjusted radiative forcing has been diagnosed via two independent methods: regression and fixed-SST. Uncertainties in these values are indicated in Figure 2.

AOGCM	Radiative Forcing (Wm^{-2})		Climate Feedback Parameter $-\alpha$ (Wm^{-2} K^{-1})				Eqm Climate Sensitivity (K)
	Fixed SST	Regression	Net	LW clear-sky	SW clear-sky	Net CRE	
CanESM2	7.35	7.67	-1.04	-1.88	0.71	0.13	3.69
CNRM-CM5	n.a.	7.43	-1.14	-1.73	0.78	-0.20	3.25
CSIRO-Mk3-6-0	6.20	5.17	-0.63	-1.70	0.84	0.23	4.08
HadGEM2-ES	6.99	5.84	-0.64	-1.66	0.65	0.37	4.58
INM-CM4	6.24	5.95	-1.43	-1.98	0.67	-0.12	2.08
IPSL-CM5A-LR	6.49	6.20	-0.75	-1.99	0.53	0.70	4.13
MIROC-ESM	n.a.	8.51	-0.91	-1.93	0.83	0.19	4.67
MIROC5	n.a.	8.25	-1.52	-1.85	0.84	-0.51	2.72
MPI-ESM-LR	8.63	8.18	-1.13	-1.79	0.71	-0.04	3.63
MRI-CGCM3	7.19	6.49	-1.25	-1.99	0.83	-0.09	2.60
NorESM1-M	n.a.	6.21	-1.11	-1.86	0.86	-0.11	2.80
Model mean	7.01	6.90	-1.05	-1.85	0.75	0.05	3.48

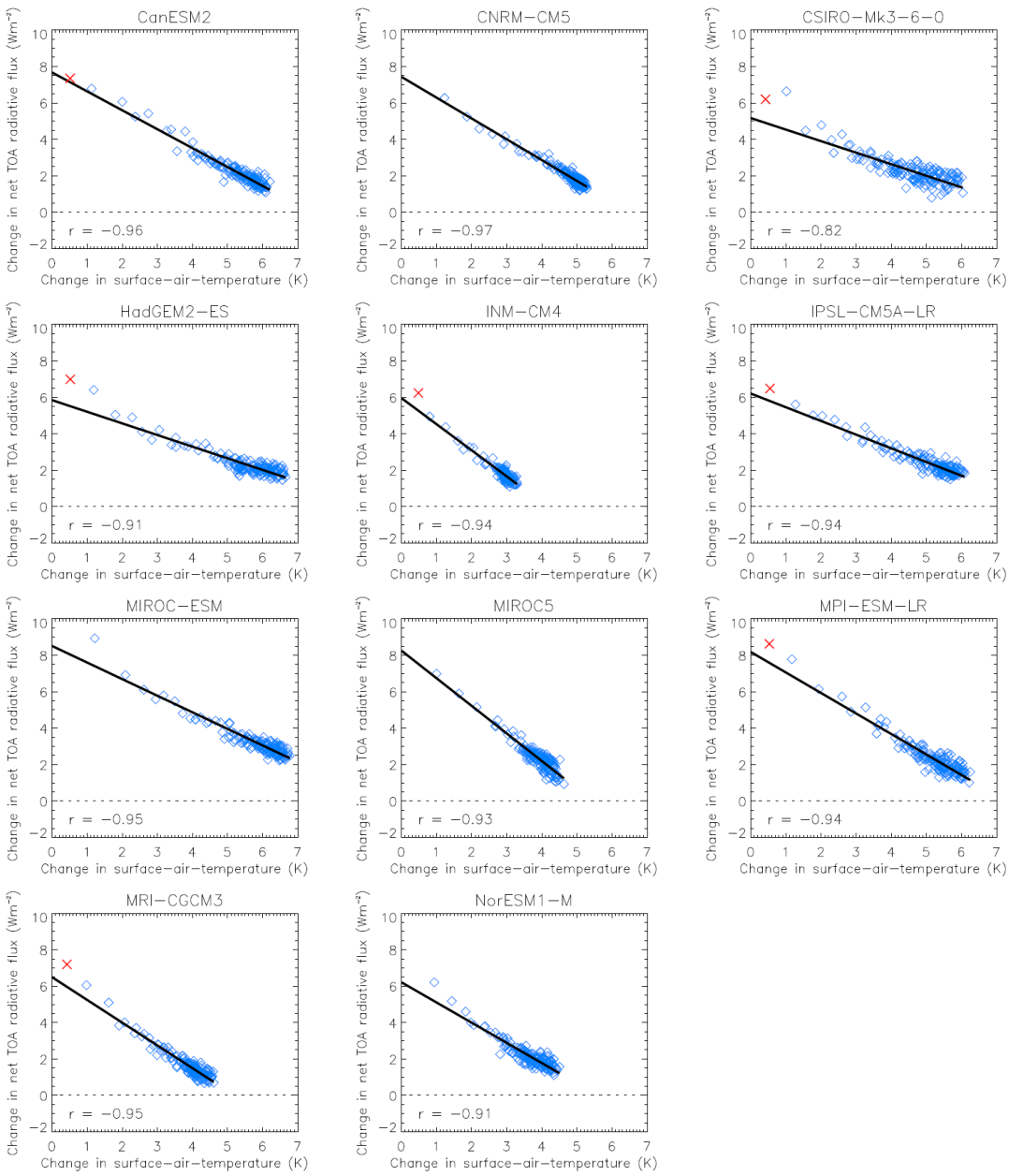

Figure 1: Relationship between *N* and Δ*T* in various CMIP5 models. Each panel shows the change in net top-of-atmosphere (TOA) radiative flux, *N*, as a function of surface-air-temperature change, Δ*T*, after an instantaneous quadrupling of CO_2. Data points are global-annual-means. Lines represent OLS regression fits to all 150 years of data (correlation coefficients are shown). Conceptually, time evolution begins at the top left of the plot, where $\Delta T = 0$ and *N* measures the adjusted radiative forcing, *F*. As the climate warms, we move rightwards and downwards as the ocean heat uptake (≈ N) decreases. The slope of the curve, $-\alpha$, measures the strength of the feedbacks in the climate system, the 'climate feedback parameter'. Equilibrium is achieved once the heat uptake reaches zero, $N = 0$, which would lie at the bottom-right of these plots, estimated by F / α. Red crosses represent an independent estimation of the $4xCO_2$ adjusted radiative forcing from fixed-SST experiments for the 7 models where this is available. These experiments largely inhibit Δ*T*, and so $F = N$. There is some land warming, giving a small but non-zero Δ*T*, as indicated on the figure.

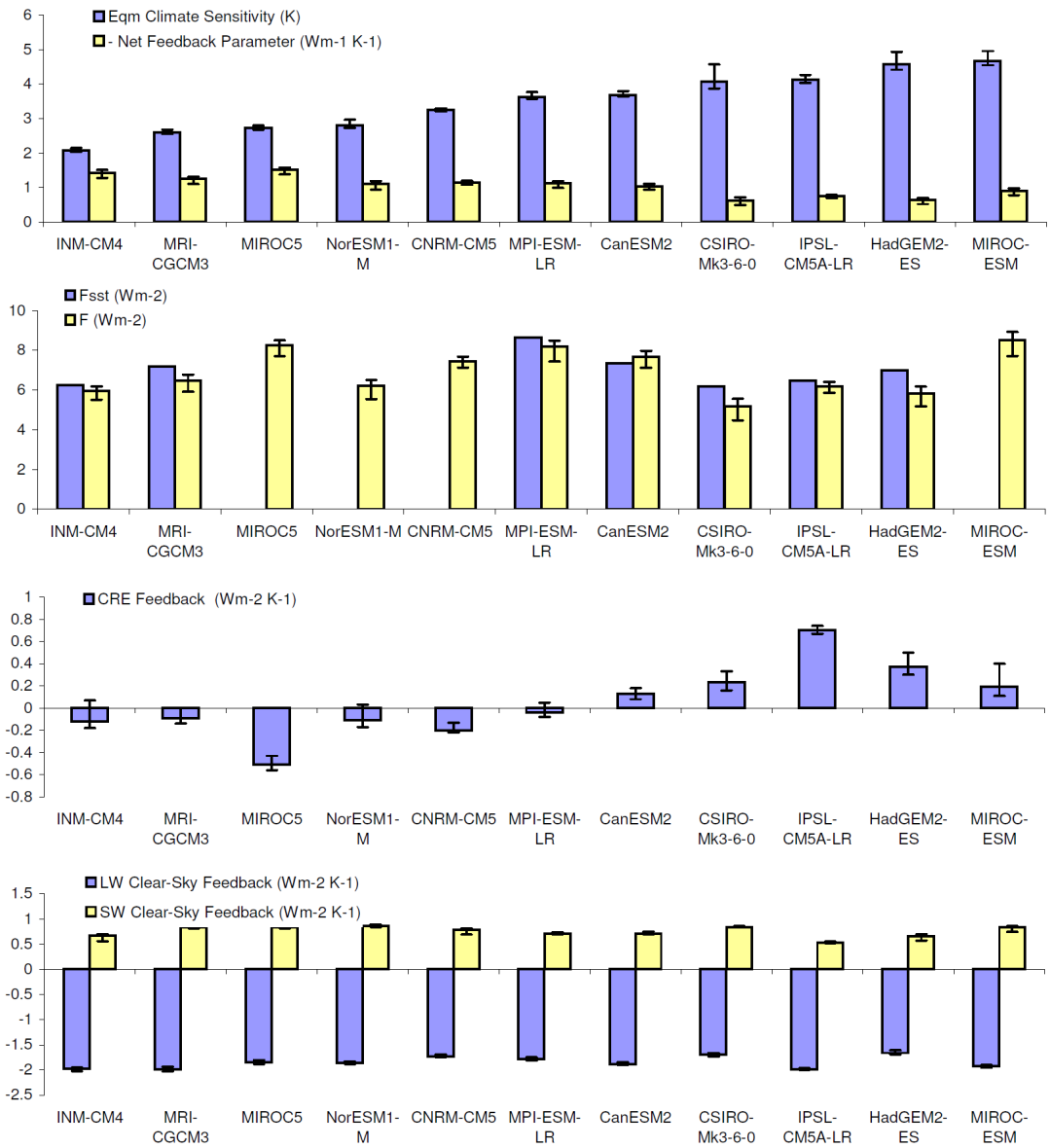

Figure 2: Comparison of the equilibrium climate sensitivity, adjusted radiative forcing and climate feedback terms. The models are ordered from left to right in order of their equilibrium climate sensitivity. Note that in the top panel α is reported, rather than $-\alpha$, to maintain the same scale. Errors bars represent 95% (2.5-97.5%) confidence interval based on bootstrapping techniques (see Methods).