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Equilibrium climate sensitivity estimated by equilibrating climate models

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25 Key Points:

• 27 simulations of 15 general circulation models are integrated to near equilibrium

• All models simulate a higher equilibrium warming than predicted by using extrapolation methods

Tropics and mid-latitudes dominate the change of the feedback parameter on different
 timescales

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31 Abstract

The methods to quantify equilibrium climate sensitivity are still debated. We collect 32 millennial-length simulations of coupled climate models and show that the global mean equi-33 librium warming is higher than those obtained using extrapolation methods from shorter 34 simulations. Specifically, 27 simulations with 15 climate models forced with a range of CO_2 35 concentrations show a median 17% larger equilibrium warming than estimated from the first 36 150 years of the simulations. The spatial patterns of radiative feedbacks change continu-37 ously, in most regions reducing their tendency to stabilizing the climate. In the equatorial 38 Pacific, however, feedbacks become more stabilizing with time. The global feedback evo-39 lution is initially dominated by the tropics, with eventual substantial contributions from 40 the mid-latitudes. Time-dependent feedbacks underscore the need of a measure of climate 41 sensitivity that accounts for the degree of equilibration, so that models, observations, and 42 paleo proxies can be adequately compared and aggregated to estimate future warming. 43

⁴⁴ 1 Estimating equilibrium climate sensitivity

The equilibrium climate sensitivity (ECS) is defined as the global- and time-mean, 45 surface air warming once radiative equilibrium is reached in response to doubling the atmo-46 spheric CO_2 concentration above pre-industrial levels. It is by far the most commonly and 47 continuously applied concept to assess our understanding of the climate system as simulated 48 in climate models and it is used to compare models, observations, and paleo-proxies (Knutti 49 et al., 2017; Charney et al., 1979; Houghton et al., 1990; Stocker, 2013). Due to the large 50 heat capacity of the oceans, the climate system takes millennia to equilibrate to a forcing, 51 but performing such a long simulation with a climate model is often computationally not 52 feasible. As a result, many modeling studies use extrapolation methods on short, typically 53 150-year long, simulations to project equilibrium conditions (Taylor et al., 2011; Andrews 54 et al., 2012; Collins et al., 2013; Otto et al., 2013; Lewis & Curry, 2015; Andrews et al., 55 2015; Forster, 2016; Calel & Stainforth, 2017). These so-called *effective* climate sensitiv-56 ities (Murphy, 1995; Gregory et al., 2004) are often reported as ECS values (Hargreaves 57 & Annan, 2016; Tian, 2015; Brient & Schneider, 2016; Forster, 2016). Research provides 58 evidence for decadal-to-centennial changes of feedbacks (e.g., Murphy (1995); Senior and 59 Mitchell (2000); Gregory et al. (2004); Winton et al. (2010); Armour et al. (2013); Prois-60 tosescu and Huybers (2017); Paynter et al. (2018)) but the behavior on longer timescales has 61

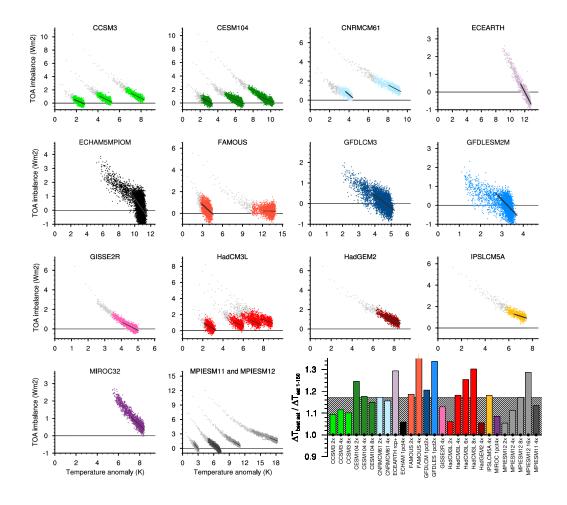


Figure 1. Evolution of global and annual mean top of the atmosphere (TOA) imbalance and surface temperature anomalies (14 small panels). The first 150 years of step forcing simulations are depicted in light gray. For experiments which are not step forcing simulations only the period after stabilizing CO₂ concentrations is shown. The black line shows the linear regression of TOA imbalance and surface warming for the last 15% of warming. The panel on the lower right shows the ratio $\Delta T_{\text{best est}} / \Delta T_{\text{est 1-150}}$, see text for definitions. A dot at the lower end of the bar indicates with 90% confidence that $\Delta T_{\text{best est}}$ and $\Delta T_{\text{est 1-150}}$ obtained by resampling 10,000 times do not overlap. The gray hashed bar in the background is the median of all simulations (1.17). FAMOUS *abrupt4x* ends outside of the depicted range at 1.53. Table 1 specifies the model versions and names, length of simulations, and numerical values for different climate sensitivity estimates.

not been compared among models. Here, we utilize LongRunMIP, a large set of millennia-62 long coupled general circulations models (GCMs) to estimate the true equilibrium warming, 63 study the centennial-to-millennial behavior of the climate system under elevated radiative 64 forcing, and test extrapolation methods. LongRunMIP is a model intercomparison project 65 (MIP) of opportunity in that its initial contributions were preexisting simulations, without 66 a previously agreed upon protocol. The minimum contribution is a simulation of at least 67 1000 years with a constant CO_2 forcing level. The collection consists mostly of doubling or 68 quadrupling step forcing simulations ("abrupt2x", "abrupt4x", ...) as well as annual incre-69 ments of 1% CO₂ increases reaching and sustaining doubled or quadrupled concentrations 70 ("1pct2x", "1pct4x"). Table 1 lists the simulations and models used here, while M. Rugen-71 stein et al. (2019) documents the entire modeling effort and each contribution in detail. 72

The equilibration of top of the atmosphere (TOA) radiative imbalance and surface 73 temperature anomaly of the simulations are depicted in Fig. 1. Throughout the manuscript, 74 we show anomalies as the difference to the mean of the unforced control simulation with 75 pre-industrial CO_2 concentrations. Light gray dots indicate annual means of the first 150 76 years of a step forcing simulation, requested by the Coupled Model Intercomparison Project 77 Phase 5 and 6 protocols (CMIP5 and CMIP6; Taylor et al. (2011); Eyring et al. (2016)) 78 and widely used to infer ECS (Andrews et al., 2012; Geoffroy, Saint-Martin, Olivié, et al., 79 2013). We refer to this timescale as "decadal to centennial". Colors indicate the "centen-80 nial to millennial" timescale we explore here. The diminishing distances to the reference 81 line at TOA = 0 indicate that most simulations archive near-equilibrium by the end of the 82 simulations. However, even if a simulation has an equilibrated TOA imbalance of near zero, 83 the surface temperature, surface heat fluxes, or ocean temperatures can still show a trend 84 (discussed in M. Rugenstein et al. (2019)). 85

Throughout the manuscript, we use " $\Delta T_{[specification]}$ " for a true or estimated equilib-86 rium warming, for a range of forcing levels not only CO_2 doubling (Table 1). We define the 87 best estimate of equilibrium warming, $\Delta T_{\text{best est}}$, as the temperature-axis intersect of the 88 regression of annual means of TOA imbalance and surface temperature anomaly over the 89 simulations' final 15% of global mean warming (black lines in Fig. 1). The lower right panel 90 in Fig.1 illustrates that all simulations eventually warm significantly more (measured by 91 $\Delta T_{best est}$) than predicted by the most commonly used method to estimate the equilibrium 92 temperature by extrapolating a least-square regression of the first 150 years of the same step 93 forcing simulation (Gregory et al., 2004; Flato et al., 2013), denoted here as " $\Delta T_{est 1-150}$ ". 94

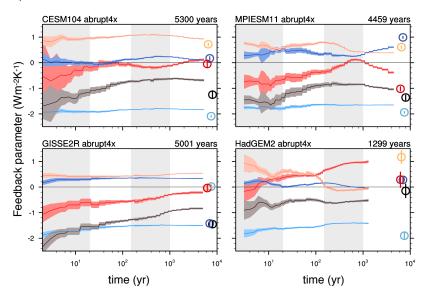
For simulations that have gradual forcings (e.g., 1pct2x), we use 150 year long step forcing 95 simulations of the same model to calculate $\Delta T_{est 1-150}$. The median increase of $\Delta T_{best est}$ 96 over $\Delta T_{est 1-150}$ is 17% for all simulations and 16% for the subset of CO₂ doubling and qua-97 drupling simulations. While $\Delta T_{est 1-150}$ implies a constant feedback parameter (the slope 98 of the regression line), other extrapolation methods allow for a time-dependent feedback pa-99 rameter, but still typically underestimate $\Delta T_{\text{best est}}$: Using years 20-150 in linear regression 100 $(\Delta T_{est 20-150}; e.g., Andrews et al. (2015); Armour (2017))$ results in median equilibrium 101 warming estimate which is 7% lower than $\Delta T_{\text{best est}}$, both for all simulations and the subset 102 of CO₂ doubling and quadrupling. The two-layer model including ocean heat uptake efficacy 103 $(\Delta T_{EBM-\epsilon}; e.g., Winton et al. (2010); Geoffroy, Saint-Martin, Bellon, et al. (2013))$ results 104 in a multi model median equilibrium warming estimate which is 9% lower then $\Delta T_{\text{best est}}$, 105 again both for all simulations and the subset of CO_2 doubling and quadrupling. Both meth-106 ods are described and illustrated in the supplemental material. 107

 $\Delta T_{best \, est}$ of any forcing level can be scaled down to doubling CO₂ levels to estimate 108 equilibrium warming for CO_2 doubling. We do so by assuming that the temperature scales 109 with the forcing level, which depends logarithmically on the CO_2 concentration (Myhre et 110 al., 1998), and assuming no feedback temperature dependence (e.g. Mauritsen et al. (2018) 111 and Rohrschneider et al. (2019), see discussion below). The estimate of equilibrium warm-112 ing for CO_2 doubling range from 2.42 to 5.83 K (excluding FAMOUS *abrupt4x* at 8.55K; 113 see Table 1 and Fig. 1). Note that the simulation abrupt4x of the model FAMOUS warms 114 anomalously strongly. As this simulation represents a physically possible result, we do not 115 exclude it from the analysis (see more details in SM Section 4). The results are qualitatively 116 the same if $\Delta T_{best est}$ is defined by regressing over the last 20% instead of 15% of warming 117 or instead time averaging the surface warming toward the end of every simulation without 118 taking the information of the TOA imbalance into account. SM Section 1 discusses different 119 options and choices to determine $\Delta T_{best est}$. 120

121

2 Global feedback evolution

¹²² Current extrapolation methods underestimate the equilibrium response because climate ¹²³ feedbacks change with the degree of equilibration (Murphy, 1995; Senior & Mitchell, 2000; ¹²⁴ Andrews et al., 2015; Knutti & Rugenstein, 2015; M. A. A. Rugenstein, Caldeira, & Knutti, ¹²⁵ 2016; Armour, 2017; Proistosescu & Huybers, 2017; Paynter et al., 2018). We define the ¹²⁶ global net TOA feedback as the *local tangent* in temperature-TOA space (δ TOA/ δ T) com-



a) Time evolution of feedbacks in four models

b) Feedback components for different time periods

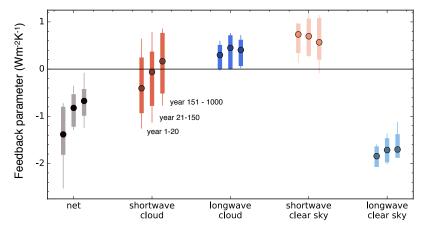


Figure 2. a) Time evolution of global feedbacks in four characteristic models. Net TOA feedback (gray) is the sum of its components: the cloud effects in the shortwave (red) and longwave (blue), and clear sky feedbacks in the shortwave (salmon) and longwave (light blue). Circles at the right of each panel indicate the feedbacks arising from internal variability; shading and vertical lines shows the 2.5-97.5% confidence intervals. Panel titles give the model name and length of the simulation. Time periods of 1-20 years and 150-1000 years are shaded gray. (b) Feedback evolution in the step forcing simulations of CCSM3, CESM104, CNRMCM6, ECHAM5MPIOM, FAMOUS, GISSE2R, HadCM3L, HadGEM2, IPSLCM5A, MPIESM11, and MPIESM12, see Table 1 for naming convention. Lines show all simulations, dots represent median values and bars spans all but the two highest and two lowest simulations. SM Fig. 4 and 5 show the feedback evolution for all available simulations.

puted by a least square regression of all global and annual means of netTOA imbalance and 127 surface temperature anomaly within a temperature bin, which is moved in steps of 0.1 K 128 throughout the temperature space to obtain the continuous local slope of the point cloud 129 (sketched out in SM Fig. 2a). We decompose the net TOA imbalance into its clear sky and 130 cloud radiative effects (CRE; e.g., Wetherald and Manabe (1988); Soden and Held (2006); 131 Ceppi and Gregory (2017)) in the shortwave and longwave (Fig. 2a). The feedbacks change 132 continuously – not on obviously separable timescales – in some models more at the begin-133 ning of the simulations (e.g., CESM104), in some models after 150 years (e.g., GISSE2R) or, 134 in some models, intermittently throughout the simulation (e.g., MPIESM11 or HadGEM2). 135 The shortwave CRE dominates the magnitude and the timing of the net feedback change, 136 and can be counteracted by the longwave CRE. The reduction of the shortwave clear sky 137 feedback associated with ice albedo, lapse rate, and water vapor is a function of tempera-138 ture and occurs on centennial to millennial timescales. Longwave clear sky changes, when 139 present, contribute to the increase of the sensitivity with equilibration time and temperature. 140 The net feedback parameter can be composed of a subtle balance of different components at 141 any time and the forced signal is not obviously linked to the feedback arising from internal 142 variability, defined by regressing all available annual and global means of TOA imbalance 143 and surface temperature anomalies (relative to the mean) of the control simulations (circles 144 in Fig. 2a; Roe (2009); Brown et al. (2014); Zhou et al. (2015); Colman and Hanson (2017)). 145 Models which are more sensitive than other models – have feedbacks which are more 146 positive – at the beginning of the simulation are generally also more sensitive towards the 147 end. The model spread in the magnitude of feedbacks does not substantially reduce in time, 148 while the feedback parameter change varies from negligible to an order of magnitude. We 149 quantify the continuous changes across models by considering different time periods, namely 150 years 1-20, 21-150, and 151-1000 (Fig. 2b), in each of which we regress all points. In addition 151 to the increase of the feedback parameter between years 1-20 and 21-150, which has been 152 documented for CMIP5 models (Geoffroy, Saint-Martin, Bellon, et al., 2013; Andrews et 153 al., 2015; Proistosescu & Huybers, 2017; Ceppi & Gregory, 2017), there is a further increase 154 from centennial to millennial timescales. 155

Previous research has shown that the change in feedbacks over time can come about through a dependence of feedback processes on the increasing temperature (Hansen et al., 1984; Jonko et al., 2013; Caballero & Huber, 2013; Meraner et al., 2013; Bloch-Johnson et al., 2015), due to evolving surface warming patterns and feedback processes ("pattern effect";

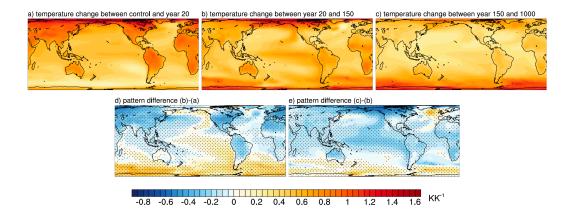


Figure 3. Multi-model mean normalized patterns of surface warming (local warming divided by global warming) between the average of (a) the control simulation and year 15-25, (b) year 15-25 and 140-160, (c) year 140-160 and 800-1000, and their differences (d and e) for the same models and simulations as in Fig. 2b. For models contributing several simulations, these are averaged. Stippling in panel d and e indicates that 9 out of 11 models agree in the sign of change.

Senior and Mitchell (2000); Winton et al. (2010); Armour et al. (2013); M. A. A. Rugenstein, 160 Gregory, et al. (2016); Gregory and Andrews (2016); Haugstad et al. (2017); Paynter et al. 161 (2018)), or both at the same time (Rohrschneider et al., 2019). There is no published method 162 which clearly differentiates between time/pattern and temperature/state dependence and 163 simulations with several forcing levels are needed to disentangle them. The relationship 164 between forcing and CO_2 concentrations is a matter of debate (Etminan et al., 2016) and 165 further complicates the analysis, as time, temperature, and forcing level dependence might 166 compensate to some degree (Gregory et al., 2015). As not all models contributed several 167 forcing levels, we focus in the following on robust pattern changes in surface temperatures 168 and feedbacks, which occur in most or all simulations irrespective of their overall tempera-169 ture anomaly or forcing level. 170

¹⁷¹ 3 Pattern evolution of surface warming and feedbacks

The evolution of surface warming patterns during the decadal, centennial, and millennial periods displays a fast establishment of a land-sea warming contrast, Arctic amplification, and the delayed warming over the Southern Ocean that have been studied on annual to centennial timescales (Fig. 3; Senior and Mitchell (2000); Li et al. (2013); Collins et al. (2013); Armour et al. (2016)). Arctic amplification does not change substantially,

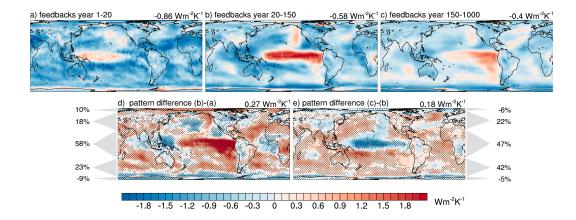


Figure 4. Time evolution of feedback patterns. Model-mean of local contribution to the change in global feedbacks (local TOA anomaly divided by global warming during the period indicated in the panel titles; see text for definitions) (a–c) and their differences (d, e). The global feedback value is shown in the panel title. Regionally aggregated contributions to the global values are indicated with percent numbers and gray triangles (22°S-22°N, 22°S/N-66°S/N, 66°S/N-90°S/N, representing 40%, 27%, and 4% of the global surface area respectively). Model and simulations selection, weighting, and stippling is the same as in Fig. 3. SM Fig. 6–12 shows all TOA components.

- whereas Antarctic amplification strengthens by approximately 50% on centennial to millennial timescales (Salzmann, 2017; M. Rugenstein et al., 2019). The warming in the northern
 North Atlantic reflects the strengthening of the Atlantic meridional overturning circulation,
 after the initial decline (Stouffer & Manabe, 2003; Li et al., 2013; M. A. A. Rugenstein,
 Sedláček, & Knutti, 2016; Rind et al., 2018; Jansen et al., 2018).
- In the Pacific, at all times, the temperatures in absolute terms are higher in the West 182 compared to the East Pacific. The eastern equatorial Pacific warms more than the warm 183 pool in most simulations, a phenomenon reminiscent of the positive phase of the El-Niño-184 Southern-Oscillation (ENSO) ("ENSO-like warming" (Song & Zhang, 2014; Andrews et al., 185 2015; Luo et al., 2017; Tierney et al., 2019)). This tendency can last several millennia, but 186 significantly reduces or stops in most simulations after a few hundred years. Similar to the 187 Equatorial east Pacific, the south east Pacific warms more than the warm pool (Zhou et al., 188 2016; Andrews & Webb, 2018). However, models display a large variance in the timescales 189 of warming in these two regions, i.e. the warm pool can initially warm faster or slower than 190 the south east Pacific.s Across the Pacific, the change in surface warming pattern is reminis-191 cent of the Interdecadal Pacific Oscillation (IPO; Fig. 3d). In many models, the reduction 192

of the Walker circulation coincides with the decadal to centennial ENSO/IPO-like warming
pattern, but it does not obviously coincide with surface warming pattern changes on the
millennial timescale, indicating that subtropical ocean gyre advection and upwelling play a
more prominent role on longer timescales (Knutson & Manabe, 1995; Song & Zhang, 2014;
Fedorov et al., 2015; Andrews & Webb, 2018; Luo et al., 2017; Zhou et al., 2017; Kohyama
et al., 2017). The mechanisms and spread of model responses in the Pacific are still under
investigation.

Feedbacks defined as the local tangent in temperature-TOA space as used in Fig. 2a 200 contain a signal from both the internal variability and the forced response. In order to 201 isolate the forced response, we take the difference of the means at the beginning and end of 202 the time periods discussed above. We call this definition of feedbacks the *finite difference* 203 approach, as it represents a change across a time period (SM Fig. 2b). Fig. 4 shows the local 204 contribution to the global net TOA changes (defined as the local change in TOA imbalance 205 divided by the global temperature change.) for the same time periods and models as used in 206 Fig. 3. In the initial years, the atmosphere restores radiative balance through increased ra-207 diation to space almost everywhere, except in the western-central Pacific (Fig. 4a), whereas 208 on decadal to centennial timescales, the structure of the feedbacks mirrors the surface tem-209 perature evolution and develops a pattern reminiscent of ENSO/IPO (Fig. 4b). The cloud 210 response dominates the pattern change, although for CMIP5 models, changes on decadal 211 and centennial timescales have been attributed to changing lapse rate feedbacks as well (SM 212 Fig. 6-8 and Andrews et al. (2015); Andrews and Webb (2018); Ceppi and Gregory (2017)). 213 For the millennial timescales, our models show that feedbacks become less negative almost 214 everywhere, switching from slightly negative to positive in parts of the Southern Ocean and 215 North Atlantic region, and become less destabilizing in the Tropical Pacific (Fig. 4c). The 216 feedback pattern change from decadal to centennial timescales (Fig. 4d) is reversed in many 217 regions on centennial to millennial timescales (Fig. 4e), particularly in the entire Pacific 218 basin, the Atlantic, and parts of Asia and North America. This "pattern flip" is dominated 219 by longwave CRE (SM Fig. 8) and mirrors, in the Pacific, the reduction in ENSO/IPO-like 220 surface warming patterns discussed for the surface temperature evolution. 221

Note that the local temperature is not part of the calculation of the local contribution
in feedback changes. Due to the far-field effects of local feedbacks (e.g., Rose et al. (2014);
Kang and Xie (2014); M. A. A. Rugenstein, Caldeira, and Knutti (2016); Zhou et al. (2016,
2017); Ceppi and Gregory (2017); Liu et al. (2018); Dong et al. (2019)), the relation between

the local feedback contribution (Fig. 4) and the local temperatures (Fig. 3) is not straight-226 forward. There is strong correspondence between changes of TOA fluxes and temperature 227 patterns in the Pacific on decadal to millennial timescales: Stronger (weaker) local warming 228 coincides with a more positive (negative) local feedback contribution. However, there is 229 no clear correspondence directly after the application of the forcing, or over land and the 230 Southern Ocean through time. SM Fig. 13 and 14 show overlays of Fig. 3 and 4 for a better 231 comparison. A local correspondence does not necessarily indicate a strong local feedback 232 (i.e. local TOA divided by local surface temperature change), as both the local TOA and 233 the surface in one region could be forced by another region. A closer investigation of local 234 and far-field influence of feedbacks is under investigation (Bloch-Johnson et al., in revision). 235

Although the spatial patterns of changing temperature and radiative feedbacks vary among models, the large scale features discussed here occur robustly across most models and forcing levels, and also occur in the 1pct2x and 1pct4x simulations, which are not included in the figures.

²⁴⁰ 4 Regions accounting for changing global feedbacks

We quantify the contribution of the tropics, extra-tropics, and polar regions to the 241 global feedback change (Fig. 4d,e) by adding up all feedback contributions of the respective 242 areas indicated by the gray triangles and expressing them as percentages of the total. We 243 note that the total is the global feedback parameter, i.e., the slope of the point clouds in 244 Fig. 1 which is indicated on the top right of each panel. These percentages reflect the role 245 played by TOA fluxes in each region, which is not the same as the role played by surface 246 warming in each region, as noted above. Whereas the tropics account for the bulk of the 247 change (58%) on decadal to centennial and 47% on centennial to millennial timescales), the 248 mid-latitudes become more important with time (Northern and Southern Hemisphere com-249 bined for 41% on decadal to centennial and for 66% on centennial to millennial timescales). 250 The high latitudes, dominated by the shortwave clear sky feedback (SM Fig. 12), play only 251 a minor role in influencing the global response at all timescales. The regional accounting 252 of global feedback changes permits us to test competing explanations regarding the spatial 253 feedback pattern by placing them in a common temporal framework. Primary regions con-254 trolling the global feedback evolution have been suggested to be the Southern Hemisphere 255 mid to high latitudes (Senior & Mitchell, 2000), the Northern Hemisphere subpolar regions 256 (Rose & Rayborn, 2016; Trossman et al., 2016), and the Tropics (Jonko et al., 2013; Mer-257

aner et al., 2013; Block & Mauritsen, 2013; Andrews et al., 2015; Ceppi & Gregory, 2019),
especially in the Pacific (Andrews & Webb, 2018; Ceppi & Gregory, 2017).

The simulations robustly shows a delayed warming in the Southern Hemisphere relative 260 to the Northern Hemisphere throughout the millennia-long integrations, which correlates 261 with the time evolution of net TOA and shortwave CRE (not shown). This behavior lends 262 support to the hypothesis of Senior and Mitchell (2000) who propose that feedbacks change 263 through time due to the slow warming rates of the Southern Ocean relative to the upper 264 atmospheric levels. This reduced lapse rate increases atmospheric static stability (and thus, 265 the shortwave cloud response) in the transient part of the simulation, but decreasingly less 266 so towards equilibrium. 267

The extra-tropical cloud response in the model-mean is non-negligible in the Southern Ocean and North Atlantic on decadal to centennial timescales, as proposed by Rose and Rencurrel (2016) and Trossman et al. (2016). However, it comes to dominate the global response only on centennial to millennial timescales and when both hemispheres are considered.

We find that the longwave clear sky feedback does moderately increase in many models as the temperature or the forcing level increases, mainly in the tropics and Northern Hemisphere mid-latitudes (Fig. 2a, SM Fig. 4, SM Fig. 5). This is in accordance with the proposed argument that the tropics govern the global feedback evolution because the water vapor feedback increases with warming (Jonko et al., 2013; Meraner et al., 2013; Block & Mauritsen, 2013; Andrews et al., 2015), possibly following the rising tropical tropopause (Meraner et al., 2013; Mauritsen et al., 2018).

Recent work has focused on the relative influence of the Pacific, specifically the relative 280 influence of temperatures of the warm pool versus compared to other regions. Feedbacks in 281 regions of atmospheric deep convections have a far-field and global effect, while feedbacks 282 in regions of atmospheric subsidence have only a local or regional influence (Barsugli & 283 Sardeshmukh, 2002; Zhou et al., 2017; Andrews & Webb, 2018; Ceppi & Gregory, 2019; 284 Dong et al., 2019). With the available fields in the LongRunMIP archive, we cannot quan-285 tify the relative importance of water vapor and lapse rate feedbacks. However, the short and 286 longwave cloud response (SM Fig. 6–8) in the models qualitatively agree with the proposed 287 change of tropospheric stability patterns on decadal to centennial timescales (Andrews & 288 Webb, 2018; Ceppi & Gregory, 2017), especially in the Pacific region. In contrast, on centen-289

nial to millennial timescales, the tropical Pacific response becomes less important compared

to the mid-latitudes and the net tropical CRE does not change anymore (SM Fig. 6).

²⁹² 5 Implications

We demonstrate that the evolution of the global feedback response is dominated by the 293 mid-latitudes on centennial to millennial and the tropics on decadal to centennial timescales. 294 The global net feedback change is a result of a subtle balance of different regions and different 295 TOA components at all times; even more so in single simulations than in the model mean 296 shown here. This motivates process-based feedback studies in individual models as well 297 as multi-model ensembles to draw robust conclusions and increase physical understanding 298 of processes. To relate the timescales and model behavior to the observational record and 299 paleo proxies a better understanding of a) the atmospheric versus oceanic drivers of surface 300 temperature patters in both, the coupled climate models and the real world and b) the local 301 and far field interactions of tropospheric stability, clouds, and surface temperatures need 302 to be achieved. Note that climate models have typical and persistent biases in regions we 303 identify as important, mainly the Equatorial Pacific, Southern Ocean and ocean upwelling 304 regions. The pattern effect of the real world might act on timescales which are different 305 than the ones of the climate models. 306

Our results show that radiative feedbacks, usually called "fast", act continuously less 307 stabilizing on the climate system as the models approach equilibrium. As a result, the 308 equilibrium warming is higher than estimated with common extrapolation methods from 309 short simulations for all models and simulations in the LongRunMIP archive. ECS has 310 been historically used as a model characterization (Charney et al., 1979), but some studies 311 propose that it is not the most adequate measure for estimating changes expected over the 312 next decades and until the end of the century (e.g., Otto et al. (2013); Shiogama et al. (2016); 313 Knutti et al. (2017)). Alternative climate sensitivity measures are the effective climate 314 sensitivity computed on different timescales, the transient climate response to gradually 315 increasing CO_2 (TCR), or the transient climate response to cumulative carbon emissions 316 (e.g., Allen and Frame (2007); Millar et al. (2015); Gregory et al. (2015); Grose et al. (2018)). 317 Beyond not being an accurate indicator of the equilibrium response, these alternative climate 318 sensitivity measures capture the models in different degrees of equilibration. We show that 319 it is an open question how different measures of sensitivity relate to each other. A recent 320 study shows that $\Delta T_{est 1-150}$ correlates better than TCR with end-of-21st-century warming 321

across model (Grose et al. (2018), see also Gregory et al. (2015)). Thus, we underscore the need of comparing models, observations, and paleo proxies on well-defined measures of climate sensitivity, which ensure they are in the same state of equilibration.

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- Fields shown in this paper can be accessed on https://data.iac.ethz.ch/longrunmip/
- GRL/. See www.longrunmip.org and M. Rugenstein et al. (2019) for more details on each
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