

# *Relationship of tropospheric stability to climate sensitivity and Earth's observed radiation budget*

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# Relationship of tropospheric stability to climate sensitivity and Earth's observed radiation budget

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**Climate feedbacks generally become smaller in magnitude over time under CO<sub>2</sub> forcing in coupled climate models, leading to an increase in the effective climate sensitivity, the estimated global-mean surface warming in steady state for doubled CO<sub>2</sub>. Here we show that the evolution of climate feedbacks in models is consistent with the effect of a change in tropospheric stability, as has recently been hypothesized, and the latter is itself driven by the evolution of the pattern of sea surface temperature response. The change in climate feedback is mainly associated with a decrease in marine tropical low cloud (a more positive shortwave cloud feedback) and with a less negative lapse rate feedback, as expected from a decrease in stability. Smaller changes in surface albedo and humidity feedbacks also contribute to the overall change in feedback, but are unexplained by stability. The spatial pattern of feedback changes closely matches the pattern of stability changes, with the largest increase in feedback occurring in the tropical East Pacific. Relationships qualitatively similar to those in the models among sea surface temperature pattern, stability, and radiative budget are also found in observations on interannual time scales. Our results suggest that constraining the future evolution of sea surface temperature patterns and tropospheric stability will be necessary for constraining climate sensitivity.**

climate sensitivity | climate feedbacks | clouds | satellite observations

How much Earth will warm in response to future greenhouse gas emissions is a fundamental question in climate science. Accordingly, a widely-used metric for the evaluation and comparison of climate models is the equilibrium climate sensitivity (ECS), the steady-state global-mean surface temperature change for a doubling of CO<sub>2</sub> concentration relative to the pre-industrial state. A common method to estimate ECS involves assuming the climate system response to a radiative forcing  $F$  to be proportional to global-mean temperature  $T$ , according to  $\lambda = (N - F)/T$  where  $\lambda < 0$  (1). Here  $N$  denotes the net downward radiative imbalance,  $N - F$  is the radiative response, and  $\lambda$  is the proportionality constant between radiative response and global-mean warming. Because its value depends on climate feedback processes involving changes in the atmospheric lapse rate, water vapor concentration, cloud properties, and surface albedo with warming, the proportionality constant  $\lambda$  is usually referred to as the climate feedback parameter. Assuming  $\lambda$  stays constant in time, we may estimate ECS by extrapolating the relationship between  $N - F$  and  $T$  to the temperature at which  $N = 0$ , i.e. radiative balance is restored:  $ECS = -F/\lambda$ , if  $F$  represents the forcing of a doubling of CO<sub>2</sub>.

Although convenient, the assumption of a constant proportionality factor  $\lambda$  between radiative response and global-mean warming does not hold perfectly in climate models. Indeed, in most climate models  $\lambda$  decreases in magnitude as time passes following an increase in CO<sub>2</sub> concentration, leading

to an increase in the “effective” climate sensitivity over time (2–13). However, the mechanisms of this evolution are currently not understood. Targeted climate model experiments have pointed to the role of evolving patterns of sea surface temperature (SST) increase in driving the evolution of climate sensitivity and feedbacks (9, 14–17), which may alternatively also be interpreted as changing patterns of ocean heat uptake (5, 18–20). Two distinct hypotheses have been proposed to link the evolution of SSTs to climate feedbacks over the course of the transient response to CO<sub>2</sub> forcing:

1. Feedbacks are assumed to scale linearly with local temperature, but are fixed in time. Global-mean feedback varies only as a result of evolving surface warming patterns, causing the spatial weighting of local feedbacks to change as time passes (7).
2. The SST evolution favors a decrease in tropospheric stability, resulting in less free-tropospheric warming per unit surface warming. This stability decrease reduces the ability of the atmosphere to cool radiatively to space from the upper troposphere (a less negative lapse rate feedback; 17), and acts to decrease low cloud cover in subsidence regions, enhancing the absorption of solar radiation (a more positive cloud feedback; 15–17). Under this hypothesis, feedbacks may vary locally in time.

Here we show that the evolution of climate feedbacks during the transient response to increased CO<sub>2</sub> in current coupled climate models is consistent with the effects of changes in

## Significance Statement

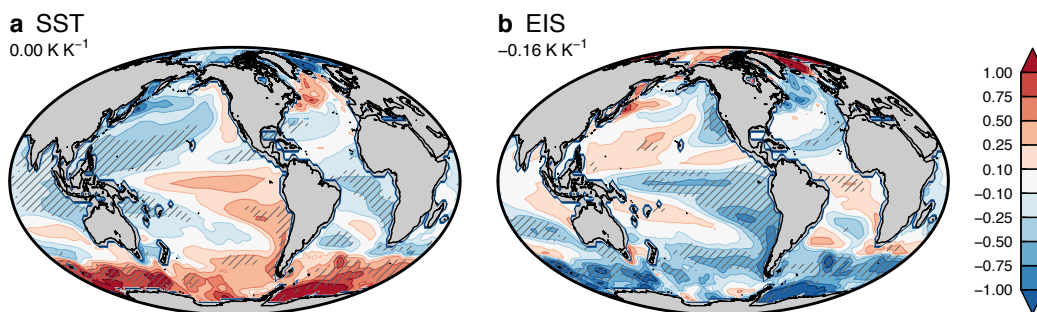
In current climate models, the anticipated amount of warming under greenhouse gas forcing, quantified by the “effective climate sensitivity”, increases as time passes. Consequently, effective climate sensitivity values inferred from the historical record may underestimate the future warming. However, the mechanisms of this increase in effective climate sensitivity are not understood, limiting our confidence in climate model projections of future climate change. Here we present observational and modeling evidence that the magnitude of effective climate sensitivity partly depends on the evolution of the vertical profile of atmospheric warming. In climate models, as the Earth warms overall, the warming becomes increasingly muted aloft, and this alters the strength of feedbacks controlling the radiative response to greenhouse gas forcing.

P.C. designed research and analyzed the data. P.C. and J.M.G. jointly wrote the paper.

The authors declare no conflict of interest.

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**Fig. 1.** Multi-model mean difference in patterns of (a) SST and (b) EIS change. The patterns of change are first calculated separately for each model for the early (years 1–20) and late (21–150) periods by regressing local annual-mean SST or EIS against global-mean annual-mean surface temperature; then the difference is calculated as late minus early period. The patterns of change in the early and late periods are shown in Fig. S1. Numbers in the top left corner of each panel denote global-mean values. Hatching denotes a multi-model mean absolute anomaly larger than one standard deviation across models.

143 tropospheric stability, following hypothesis 2 above. Furthermore, we demonstrate that observed interannual relationships between SST pattern, tropospheric stability, and the radiative budget qualitatively support the relationships found in climate models. Our results therefore suggest that constraining climate sensitivity will require constraints on the long-term evolution of SST and tropospheric stability.

## 151 Results

### 153 Changes in the evolution of SST and tropospheric stability.

154 We first consider the SST evolution during the first 150 years following a quadrupling of CO<sub>2</sub> concentration in a set of 15 coupled climate models (Materials and Methods; Table S1). The changes over the course of the simulations are defined as the difference in responses between years 1–20 (hereafter “early period”) and years 21–150 (“late period”). As the planet warms, the pattern of SST response per unit global warming evolves towards enhanced warming in the tropical East Pacific, in the Southern Ocean, in the North Atlantic, and to a lesser extent in the Northeast Pacific, while the tropical West Pacific, Northwest Pacific, tropical Atlantic, and much of the Indian Ocean experience reduced warming relative to the global average (Fig. 1a). The global-mean difference between patterns of SST change is very close to zero. (The global-mean difference between patterns of surface temperature change, including land areas, would be exactly zero by construction.) The overall spatial structure of the SST evolution is reasonably robust among models (hatching in Fig. 1a). The characteristics of the SST evolution are also similar to those found in previous studies using different sets of climate models (7, 9, 21). The delayed warming in the East Pacific and in the Southern Ocean is broadly consistent with the effects of upwelling (22, 23), but additional coupled ocean-atmosphere processes likely contribute to the evolution of the SST pattern (22, 24).

179 We now provide evidence that the evolution of the SST warming pattern favors a decrease in tropospheric stability. As a stability metric, we use the estimated inversion strength (EIS; 25), a measure of the strength of the inversion at the top of the boundary layer based on the difference in potential temperature between the surface and 700 hPa. EIS accounts for the temperature dependence of the moist adiabat to quantify the effective stability of the lower troposphere, and is tradition-

205 ally defined over ocean regions only. In observations, EIS is strongly correlated with marine low cloud cover in subsidence regions (25), consistent with the notion that a stronger inversion is more effective at trapping moisture in the boundary layer.

210 How do we expect the SST pattern to affect tropospheric stability? At any point in space, the stability change depends on the relative change in surface and free-tropospheric temperature. In the tropics, free-tropospheric temperature is largely set by the evolution of SST in warm, convective regions, such as the West Pacific warm pool, where the lapse rate is pegged to a moist adiabat owing to moist convection (26, 27). This constraint implies that the warmest regions should always remain nearly neutrally stable. Away from warm convective regions, however, the stability response will roughly depend on the ratio of local SST change to SST change in the warm pool (15). If local SST increases more than in the warm pool, stability will decrease because the free-tropospheric temperature will increase less than predicted by a local moist adiabat; the opposite would be true if local SST increased less than in the warm pool. While strictly speaking the constraint on free-tropospheric temperature applies to the tropics only, extratropical free-tropospheric temperature should be influenced by SST changes in warmer convective regions, so that a similar argument can be applied to qualitatively interpret extratropical stability changes. Although we argue that the SST pattern is the main control on the time evolution of tropospheric stability in our model simulations, additional processes can also affect stability as quantified by EIS – for example land-sea temperature contrasts and CO<sub>2</sub> concentrations (28).

235 The differences in stability response between the early and late periods in Fig. 1b are consistent with the above reasoning. The EIS difference in the warm pool around the Maritime Continent is small. Because the warm pool is warming less than average, the EIS response becomes more negative in most other regions; the larger the relative warming, the larger the stability decrease. This yields a global-mean decrease in the response of tropospheric stability to warming. It is noteworthy that the global-mean EIS response becomes more negative as time passes in all models included in this analysis (Fig. S2a).

247 **Changes in climate feedbacks.** We will now show that the evolution of climate feedbacks is consistent with the changes in

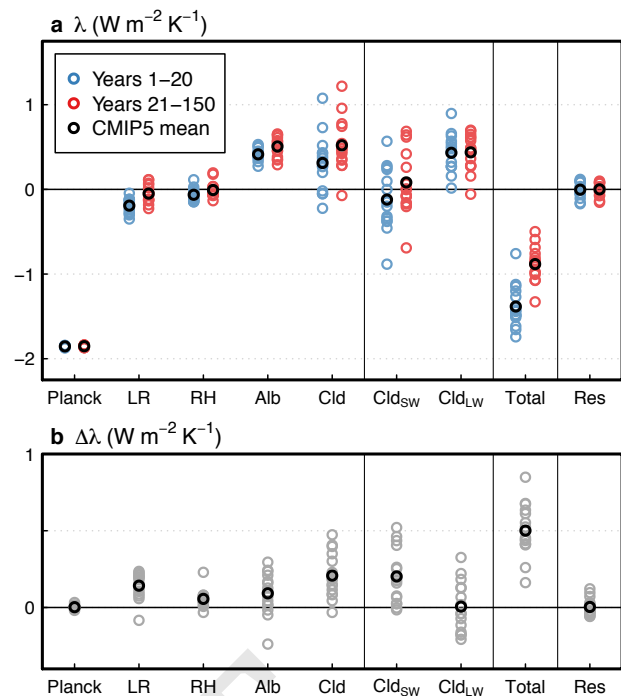
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249 tropospheric stability over the course of the transient response  
 250 to CO<sub>2</sub> forcing. Figure 2 shows the changes in global-mean  
 251 feedback parameter decomposed into the contributions of tem-  
 252 perature, water vapor, surface albedo, and clouds (using radiative  
 253 kernels; Materials and Methods). On average, the total  
 254 feedback increases by 0.50 W m<sup>-2</sup> K<sup>-1</sup> (-1.38 to -0.88 W  
 255 m<sup>-2</sup> K<sup>-1</sup>), consistent with previous findings (9). Consequently,  
 256 the estimated ECS increases by 0.57 K on average (2.83 to  
 257 3.40 K; Fig. S2b). The change in feedback is primarily due to  
 258 the effect of clouds (0.21 W m<sup>-2</sup> K<sup>-1</sup>), followed by the lapse  
 259 rate feedback (0.14 W m<sup>-2</sup> K<sup>-1</sup>), with smaller contributions  
 260 of changes in surface albedo (0.09 W m<sup>-2</sup> K<sup>-1</sup>) and relative  
 261 humidity (0.06 W m<sup>-2</sup> K<sup>-1</sup>). The increase in cloud feedback  
 262 is almost entirely due to a change in shortwave reflection (0.20  
 263 W m<sup>-2</sup> K<sup>-1</sup>). Since the mean residual is near zero, it does  
 264 not contribute to the change in total feedback parameter.

265 The results in Fig. 2 are thus consistent with the expected  
 266 effect of a stability decrease following hypothesis 2: a decrease  
 267 in low cloud amount (causing a more positive shortwave cloud  
 268 feedback), and a less negative lapse rate feedback, these two  
 269 effects jointly accounting for most of the increase in feedback  
 270 parameter and climate sensitivity. While changes in factors  
 271 other than stability – particularly local SST, subsidence, and  
 272 free-tropospheric humidity – may also affect the evolution  
 273 of the cloud response to global warming (29, 30), previous  
 274 evidence from climate model experiments suggests that the  
 275 stability effect dominates the cloud response to evolving tropi-  
 276 cal SST patterns (15). In further support for this conclusion,  
 277 the relationship between tropospheric stability and feedbacks  
 278 broadly holds across models: a larger stability decrease is as-  
 279 sociated with a larger increase in feedback parameter (Fig. S3,  
 280 Text S1–S2). Stability changes account for less than half  
 281 of the inter-model spread in net feedback changes, however  
 282 ( $r^2 = 0.40$ , Fig. S3a), indicating that effects other than stabil-  
 283 ity must also contribute to this spread (Text S2).

284 The joint effect of cloud and lapse rate feedbacks accounts  
 285 for about 70% of the change in net feedback in our set of mod-  
 286 els, leaving part of the change unexplained. We have calculated  
 287 how much of the evolution in global feedback parameter can  
 288 be ascribed to a change in spatial weighting of local feed-  
 289 backs as the warming pattern evolves, following hypothesis  
 290 1 (Fig. S4). The result suggests that the increases in surface  
 291 albedo and relative humidity feedbacks are in part associated  
 292 with the evolution of the warming pattern (0.05 and 0.04 W  
 293 m<sup>-2</sup> K<sup>-1</sup> respectively; Text S3). While the increase in sur-  
 294 face albedo feedback is consistent with the evolution towards  
 295 enhanced high-latitude warming (Text S3; 7), the mechanisms  
 296 of change in global relative humidity feedback (via either of  
 297 the hypotheses or alternative mechanisms) remain unknown.

298 The linkage between climate feedbacks and tropospheric  
 299 stability is particularly striking when considering the spatial  
 300 distribution of the changes. Generally speaking, the feedbacks  
 301 become more positive in regions where the EIS response de-  
 302 creases (compare Figs. 1b and 3), and vice-versa. The largest  
 303 increase in feedback parameter occurs in the tropical Central  
 304 and East Pacific, where the EIS response becomes substan-  
 305 tially more negative as the planet warms. Although the EIS  
 306 change over the Southern Ocean is comparable or larger in  
 307 magnitude, the local change in cloud feedback is generally  
 308 small; this may be because processes unrelated to tropospheric  
 309 stability dominate the cloud response to warming at high  
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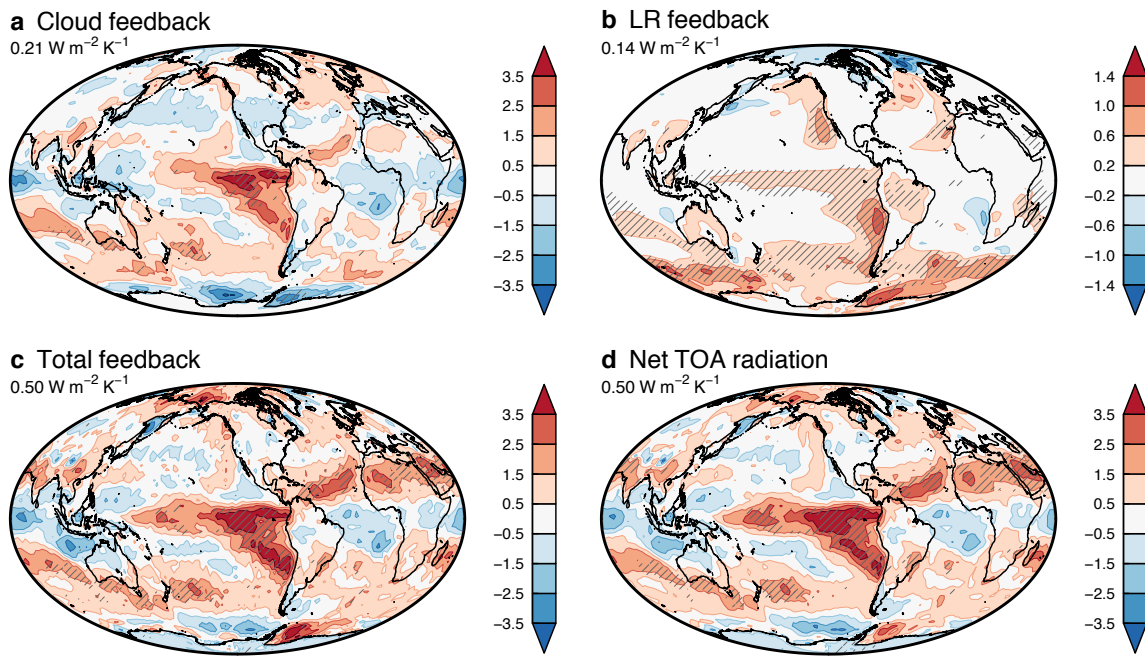
**Fig. 2.** Global-mean feedback parameter, calculated by the Gregory method (1), decomposed into contributions from uniform vertical warming (Planck feedback), non-uniform vertical warming (lapse rate), and clouds. The cloud term is further broken down into shortwave and longwave changes. “Total” refers to the sum of the feedbacks; the residual is the difference between the sum of the kernel-derived feedbacks and the actual feedback based on net top-of-atmosphere radiation (Materials and Methods). Shown are (a) the feedbacks calculated separately for the early (years 1–20) and late (21–150) periods, and (b) the difference taken as late minus early period. Blue, red and gray circles denote individual models (Table S1), while black circles are mean values.

southern latitudes. Comparing panels (c) and (d) in Fig. 3 confirms that the feedback decomposition accurately captures the actual evolution of changes in top-of-atmosphere net radiation, so that the spatial feedback patterns are not artifacts of the methodology.

**Observed relationship between tropospheric stability and radiative budget.** We have shown the existence of a relationship between SST pattern, tropospheric stability, and the radiative budget in climate models. Can a similar link be observed in the real world to confirm the realism of the modeled responses? Reliable satellite observations of the Earth’s radiative budget are too short to allow for meaningful trend calculations. However, the proposed relationship between long-term changes in stability and radiative balance may also hold in the context of interannual variations. Climate models show qualitatively similar interannual relationships between SST, EIS and the radiative budget in the context of unforced variability to those found at decadal time scales under abrupt CO<sub>2</sub> quadrupling (compare Figs. 1, 3, and S5). In the following, we will demonstrate from observations that real-world year-to-year fluctuations in tropospheric stability are associated with SST and radiative anomalies consistent with the evolution of these variables in climate models.

Figure 4 shows the patterns of SST, EIS, cloud-radiative effect (CRE, defined as all-sky minus clear-sky net down-

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**Fig. 3.** Multi-model mean spatial patterns of changes in climate feedback, calculated as late (years 21–150) minus early (1–20) period. The total feedback in (c) is the sum of the kernel-derived feedbacks (Materials and Methods), while (d) shows the actual feedback based on the regression of net top-of-atmosphere radiation onto global-mean surface temperature. Numbers in the top left corner of each panel denote global-mean values. Hatching denotes a multi-model mean anomaly larger than one standard deviation.

ward top-of-atmosphere radiation), and net downward top-of-atmosphere radiation, all regressed onto annual- and global-mean EIS anomalies, using 16 years of gridded observational and reanalysis data (note that global-mean EIS excludes regions poleward of 50°; Materials and Methods). Since the regression coefficients would represent changes consistent with a 1-K global-mean EIS increase, we multiply the coefficients by the multi-model mean change in the derivative of EIS with respect to global-mean surface temperature ( $-0.16 \text{ K K}^{-1}$ ; Fig. 1b), to obtain observed anomalies comparable in sign and magnitude with the model ensemble. Note that the impact of any changes in global-mean surface temperature has been regressed out (Materials and Methods), to minimize the contribution of the Planck response to the global-mean radiative anomalies. The observed SST pattern associated with an EIS decrease features positive SST anomalies in the tropical and subtropical East Pacific (Fig. 4a). Although no substantial cooling is observed in the warm pool, the anomalous east–west SST gradient across the tropical Pacific is in broad qualitative agreement with the difference between patterns of SST change in climate models (Fig. 1a), causing a decrease in stability in the East Pacific (Fig. 4b).

Consistent with observed relationships between EIS and low cloud, the EIS decrease coincides with a region of positive CRE anomaly, which is reflected in the net top-of-atmosphere radiative change (Fig. 4c–d). The net observed global radiative anomaly ( $0.62 \text{ W m}^{-2} \text{ K}^{-1}$ ) is larger than the multi-model-mean radiative response associated with a  $-0.16 \text{ K K}^{-1}$  EIS change ( $0.50 \text{ W m}^{-2} \text{ K}^{-1}$ ); however, considering the differences in observed SST and EIS patterns relative to the forced climate change signal in models (compare Fig. 1 with Fig. 4a–b), and given the relatively low signal-to-noise ratio in the

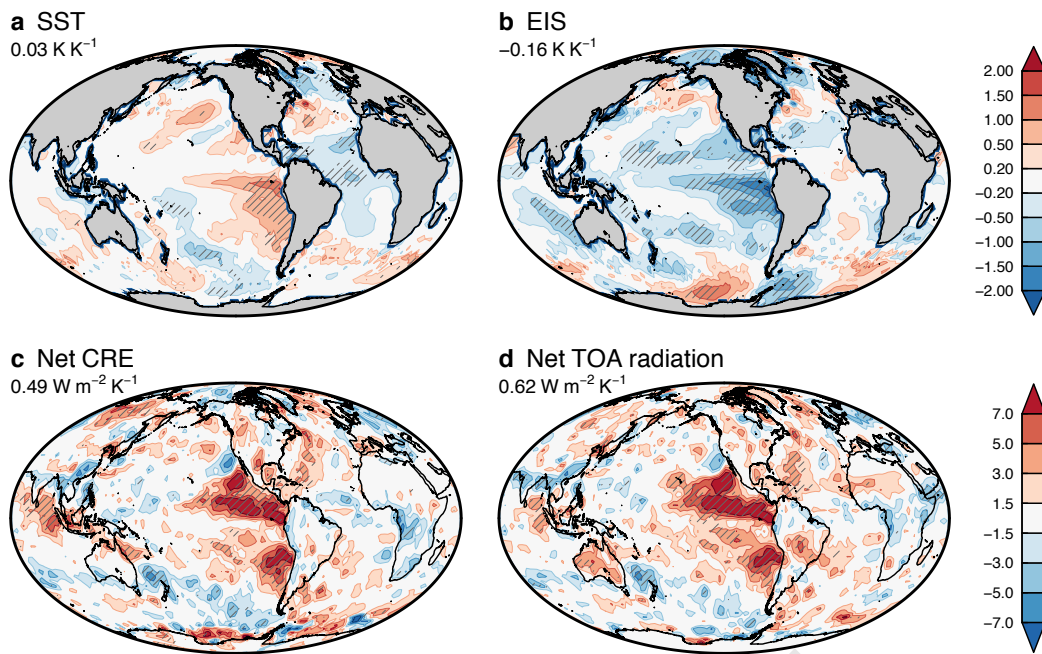
short observational record of 16 years, the agreement between observations and models should be interpreted qualitatively, rather than quantitatively. In further support of our findings, similar relationships between tropical SST pattern and low cloud amount have been observed in the context of decadal trends over the 1983–2005 period (15).

CRE anomalies can be affected not only by changes in clouds, but also by non-cloud anomalies in temperature, moisture and surface albedo. By adjusting the CRE anomalies for non-cloud factors (Materials and Methods), we confirm the contribution of clouds to the stability-induced interannual radiative anomalies in observations and models (Figs. S6a, S7a). Decomposing the stability-induced radiative changes into individual components using kernels, we find that lapse rate changes also contribute to the positive radiative anomalies in the East Pacific and in the global mean (Figs. S6b, S7b), but note that the total kernel-derived radiative changes overestimate the actual observed radiative anomalies by about 13% (Fig. S6c–d). Differences between kernel-derived and observed anomalies could be associated with errors in reanalysis temperature and moisture data, inaccuracies in the radiative kernel method (31, 32), or errors in satellite radiances (33). Despite these limitations, our observational analysis does qualitatively support the notion that decreasing tropospheric stability promotes a decrease in radiative cooling to space through changes in clouds and tropospheric lapse rate, consistent with the evolution towards higher effective climate sensitivity in CO<sub>2</sub>-forced climate model experiments.

## Summary and Discussion

Climate models predict that, as the planet warms, the response of tropospheric stability to global warming will gradually be

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**Fig. 4.** Anomalies of (a) SST, (b) EIS, (c) net CRE, and (d) net top-of-atmosphere radiation regressed onto global- and annual-mean EIS anomalies, for the period December 2000–November 2016 based on global gridded observational and reanalysis datasets (Materials and Methods). The regression coefficients are rescaled by a factor of  $-0.16 \text{ K K}^{-1}$  EIS change, to aid comparison with the results in Figs. 1 and 3. Numbers in the top left corner of each panel denote global-mean values. Hatching indicates a statistically significant regression coefficient at the 5% level.

come more negative, in a manner determined by the evolution of SSTs. The change in stability favors a decrease in low cloud cover (a positive shortwave cloud feedback) and a less negative lapse rate feedback. Although these effects dominate, part of the increase in net feedback (mainly due to changes in surface albedo and humidity) cannot be simply explained by the change in stability; these additional contributions result either from a change in the spatial weighting of local feedbacks (7), or from other unexplained mechanisms. The evolution of climate feedbacks exhibits a spatial structure that closely matches the distribution of stability changes, being most pronounced in the tropical East Pacific, a region characterized by relatively low SST, stable conditions, and extensive marine low cloud. We further show that qualitatively similar relationships between SST pattern, tropospheric stability, and the radiative budget are found in observations on interannual time scales. Therefore, to the extent that future patterns of SST change resemble those of past variability, observational evidence is consistent with the evolution towards a higher effective climate sensitivity during the transient response to CO<sub>2</sub> forcing in climate models.

Further work is needed to fully understand the implications of SST anomaly patterns for tropospheric stability and the Earth's radiative budget. In particular, the relative importance of anomalous zonal SST gradients within the tropics versus anomalous meridional gradients between tropics and extratropics remains unknown. While our results suggest a crucial role for zonal gradients within the tropical Pacific, previous work has suggested that anomalous meridional SST gradients (or relatedly, anomalies in the meridional gradient of ocean heat uptake) could have large impacts on climate

feedbacks (18–20). Further model experiments with idealized (18, 19) and realistic (14, 15, 19, 34) SST anomaly patterns will provide additional insight into the relationships between global anomalies in SST, stability, and the radiative budget.

## Materials and Methods

**Model data.** The evolution of SST, EIS, and climate feedbacks is analyzed in Coupled Model Intercomparison Project phase 5 (CMIP5) climate model output during the 150 years following abrupt quadrupling of atmospheric CO<sub>2</sub> concentrations starting from pre-industrial conditions (the “abrupt4xCO<sub>2</sub>” experiment). We analyze monthly-mean values of temperature, specific humidity, surface albedo, and upward and downward radiative fluxes at the top of atmosphere (TOA) for both all- and clear-sky conditions. The 25 models with available data are listed in Table S1. To remove any potential model drift, anomalies are calculated by subtracting the pre-industrial (pi-Control) integration from the corresponding parallel abrupt4xCO<sub>2</sub> integration. Only the first ensemble member is used for each model.

**Feedback analysis.** The contributions of temperature, moisture, surface albedo, and clouds to changes in TOA radiation are diagnosed separately for each month of the abrupt4xCO<sub>2</sub> integration using radiative kernels (31, 32). Kernels are partial derivatives of the TOA radiative flux relative to temperature, water vapor mixing ratio, and surface albedo at each model grid point. Multiplying the kernels by the changes in each of these variables provides an estimate of their contributions to TOA flux changes. Water vapor changes are partitioned into changes consistent with constant relative humidity (included in the temperature feedbacks), and changes in relative humidity (35). The kernels are also used to adjust cloud-radiative effect (CRE) anomalies for changes in non-cloud effects to obtain an estimate of the radiative changes due to clouds only (31). In this study we use kernels calculated with the Community Atmospheric Model version 5 (36).

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621 The kernel-derived contributions to TOA flux anomalies are  
622 aggregated into annual-mean values for each model, and converted  
623 to feedbacks by regressing the radiative flux time series onto global-  
624 mean surface air temperature (1, 37). Ordinary least-squares re-  
625 gressions are calculated separately for years 1–20 and 21–150 of the  
626 abrupt4xCO<sub>2</sub> experiment (9). We verify the accuracy of the kernel-  
627 derived feedbacks by a clear-sky linearity test (32, 37), whereby we  
628 compare the kernel-based sum of clear-sky TOA feedbacks with the  
629 actual clear-sky feedback obtained by regressing clear-sky net TOA  
630 radiation onto global-mean surface temperature. In our results we  
631 only include the 15 models for which the error in kernel-based clear-  
632 sky feedback is less than 15% of the actual value in both regression  
633 periods (bolded model names in Table S1; 37). (Since CRE anom-  
634 alies are based on model output, testing the kernel decomposition  
635 with clear-sky feedbacks ensures that only kernel-derived quantities  
636 are used in the test (32).) The results of the feedback analysis  
637 remain qualitatively unchanged if we include models with clear-sky  
638 errors larger than 15% in the calculations (Table S1), or if we use an  
639 alternative set of radiative kernels (31). The feedback residuals are  
640 computed as actual minus sum of kernel-derived feedbacks (where  
641 the actual feedback is the regression slope of net TOA radiation  
642 against global-mean temperature). ECS values (Fig. S2b) are cal-  
643 culated as the  $x$ -intercepts of the least-squares fits over years 1–20  
644 and 21–150.

645 **Effect of EIS variations.** The impact of year-to-year variations in tropo-  
646 spheric stability on the radiative budget is assessed by regression  
647 analysis in observations and pre-industrial model integrations (using  
648 50 years of data for each model). As a simple measure of large-scale  
649 stability changes, we use global-mean EIS, but excluding grid points

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683 poleward of 50°; including those grid points tends to emphasize  
684 high-latitude changes at the sea ice margins in climate models, likely  
685 related to sea ice variability. Since global-mean surface temperature  
686 anomalies associated with EIS variability will not generally be zero,  
687 a component of the associated radiative changes will be due to a  
688 Planck response that is not a direct result of the stability-driven  
689 cloud and lapse rate responses. Therefore, the fields are jointly  
690 regressed onto annual global-mean temperature and EIS anomalies  
691 to isolate the EIS effect, and we present results for the regression  
692 slopes associated with EIS only.

693 **Observations.** We use Clouds and the Earth's Radiant Energy Sys-  
694 tem (CERES) monthly gridded global satellite observations of all-  
695 and clear-sky TOA radiative fluxes during December 2000 – Novem-  
696 ber 2016. Prior to analysis the values are detrended at each grid  
697 point by removing a linear trend estimated by least-squares re-  
698 gression. To estimate the relationship between SST, EIS, and the  
699 observed radiative budget, we use ERA-Interim (38) reanalysis fields  
700 of surface and atmospheric temperature, with which we compute  
701 annual detrended SST and EIS anomalies. In addition to reanalysis  
702 temperature, we also use moisture and surface albedo reanalysis  
703 values in combination with radiative kernels to decompose the TOA  
704 radiative flux anomalies, and to adjust the CRE anomalies for  
705 non-cloud effects.

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# Supporting information for “Relationship of tropospheric stability to climate sensitivity and Earth’s observed radiation budget”

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## Supporting Information (SI)

**Text S1: Change in global feedback versus change in global EIS response.** In our calculation of the relationships between the changes in cloud feedback and the changes in global EIS response per unit warming, one model, MIROC-ESM, clearly stands out as an outlier (red circles in Fig. S3). This model features both the most positive change in EIS response, and the most positive change in shortwave and net cloud feedback. In a previous analysis of the relationships between shortwave cloud-radiative effect and meteorology in tropical subsidence regions, MIROC-ESM was the only CMIP5 model to simulate a substantial *positive* relationship between shortwave cloud-radiative effect and EIS (30, their Figs. 2b and S1), consistent with Fig. S3d and contrary to observational evidence.

We have therefore excluded MIROC-ESM from the calculation of the slopes and correlation coefficients in Fig. S3. Including MIROC-ESM would result in a much weaker correlation coefficient between change in cloud feedback and change in EIS response ( $r = [-0.34, -0.18]$  for the shortwave and net components, respectively).

Finally, note that the *positive* relationship between longwave cloud feedback changes and changes in EIS response (Fig. S3e) is not inconsistent with our reasoning, considering that shortwave and longwave cloud feedbacks are generally anticorrelated. The shortwave impact of stability changes dominates the spread in net cloud feedback (Fig. S3f), consistent with our understanding that the inter-model spread in cloud feedbacks is mainly associated with low clouds.

### Text S2: Inter-model spread in climate feedback changes.

The relationships in Fig. S3 suggest that inter-model differences in the evolution of tropospheric stability (as quantified by EIS) contribute to differences in the evolution of the climate feedbacks. However, the substantial scatter in Fig. S3 indicates that global-mean stability changes cannot fully account for the inter-model spread in feedback changes. Here, we briefly discuss other possible contributions to the spread in feedback changes.

First, the sensitivity of climate feedbacks to stability changes is expected to vary from model to model. This applies particularly to cloud feedbacks, since the sensitivity of low clouds to stability changes varies considerably among CMIP5 models (e.g., 30, their Fig. 1). Hence, even if the cloud feedback changes were driven entirely by changes in tropospheric stability in all climate models, we would not obtain a perfect linear relationship in Fig. S3.

Second, processes unrelated to stability must contribute to the evolution of climate feedbacks. For example, the spread in albedo feedback changes is large in our set of models (Fig. 2b) and it is unrelated to the global-mean EIS change index used in Fig. S3 ( $r = -0.02$ ). The evolution of albedo feedbacks is likely related to the evolution of the local SST response per

degree global warming in different models, as suggested by Fig. S4. Cloud responses are controlled by a variety of environmental factors other than stability (e.g., 29). Furthermore, as discussed in the main text, the mechanisms of the evolution of the relative humidity feedback remain unknown; the spread in relative humidity feedback change is only marginally related to the EIS index considered here ( $r = -0.27$ ).

### Text S3: Climate feedbacks based on the local feedback perspective.

One hypothesis for the evolution of the feedback parameter is based on the idea that the spatial pattern of warming determines the relative contributions of local feedbacks to the global-mean radiative budget; consequently, a change in the spatial warming pattern will cause a change in the global feedback parameter if the local feedbacks vary in space (7). In this perspective, the increasing global-mean feedback in global warming simulations as time passes results from the evolution of the surface warming pattern towards enhanced warming in regions of relatively positive local feedbacks. In this section, we demonstrate that this perspective cannot adequately explain the time evolution of the global feedback parameter seen in CMIP5 experiments.

In the local feedback perspective, climate feedbacks are assumed to be constant in time, but spatially varying (i.e. they depend on geographical location  $x$ ). The effective global-mean feedback  $\lambda_{\text{eff}}$  can then be understood as a spatial average of local feedbacks  $\lambda(x)$  weighted by the local contributions to global-mean warming:

$$\lambda_{\text{eff}}(t) = \overline{\lambda(x)P(x, t)}, \quad [1]$$

where  $P(x, t)$  is the normalized warming pattern (defined as local surface warming per unit global warming) and overbars denote spatial averages. Under the assumption of time-independent local feedbacks, any temporal variations in the effective global-mean feedback parameter must arise from variations in  $P(x, t)$ .

We first derive the local feedbacks  $\lambda(x)$ . Since they are assumed constant, we may calculate them using any part of the experiment; we compute them by taking the mean of the last 20 years of the abrupt4xCO2 integrations, minus the mean of the first 10 years. This ensures that rapid adjustments are excluded from the calculation, while maximizing the warming-induced signal. We divide the time-mean kernel-derived radiative anomalies at each point (for each of the components shown in Fig. S4) by the time-mean local surface temperature anomaly. This procedure yields better results than regressing the local radiative anomalies against local warming, because the low signal-to-noise ratio in local radiative anomalies means that the regression slopes are noisy and not robust. Note that for some models, the surface temperature response may be near zero in some regions, resulting in large, unphysical local feedback values when dividing the radiative anomalies by the

125 temperature anomalies. However, we have verified that these  
126 unphysical values have relatively little impact on the global-  
127 mean feedback values, and similar results are obtained if these  
128 grid points are excluded from our calculations.

129 Effective global-mean feedbacks are then calculated for  
130 years 1–20 and 21–150 following Eq. 1. The warming patterns  
131  $P(x, t)$  are calculated by regressing local surface air tempera-  
132 ture onto global-mean surface air temperature over each of the  
133 two periods. As shown in Fig. S4, the total effective global feed-  
134 back derived assuming constant local feedbacks only weakly  
135 increases in time ( $0.05 \text{ W m}^{-2} \text{ K}^{-1}$  in the multi-model mean).  
136 This means that a change in spatial weighting of constant local  
137 feedbacks can only play a secondary role for the evolution of  
138 the relationship between global-mean radiative imbalance and  
139 global-mean temperature; this evolution must result primarily  
140 from changes in the local feedbacks, rather than from changes  
141 in the spatial pattern of warming.

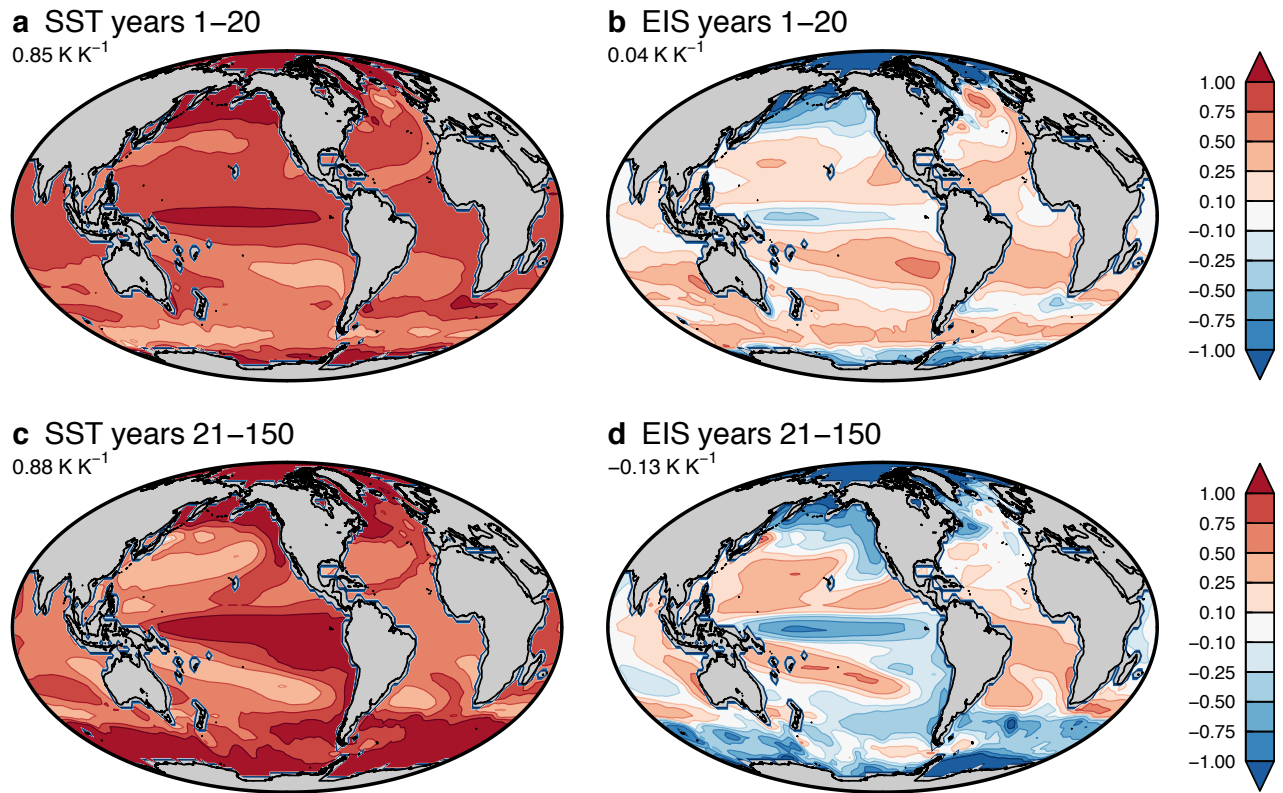
142 The results do suggest, however, that a linear dependence

187 of feedback processes on local temperature may partly explain  
188 the evolution of the surface albedo feedback ( $0.05 \text{ W m}^{-2}$   
189  $\text{K}^{-1}$ ). This is unsurprising, since the warming pattern evolves  
190 towards enhanced high-latitude warming over time (Fig. 1; 7).  
191 We have not investigated the mechanism for the weak increase  
192 in relative humidity feedback obtained assuming constant local  
193 feedbacks ( $0.04 \text{ W m}^{-2} \text{ K}^{-1}$ ). We also note that changes in  
194 the spatial weighting of local feedbacks may account for a  
195 substantial fraction of the increase in global feedbacks in a  
196 few of the models (Fig. S4b).  
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198 Note that even though Fig. S4 indicates that the hypoth-  
199 esis of constant local feedbacks cannot capture the increase  
200 in global cloud feedback over time, it may still explain the  
201 evolution of cloud feedback in some regions, where the cloud  
202 feedback processes are mainly controlled by local temperature  
203 rather than by remote factors – for example phase change  
204 feedbacks in high-latitude regions (39).  
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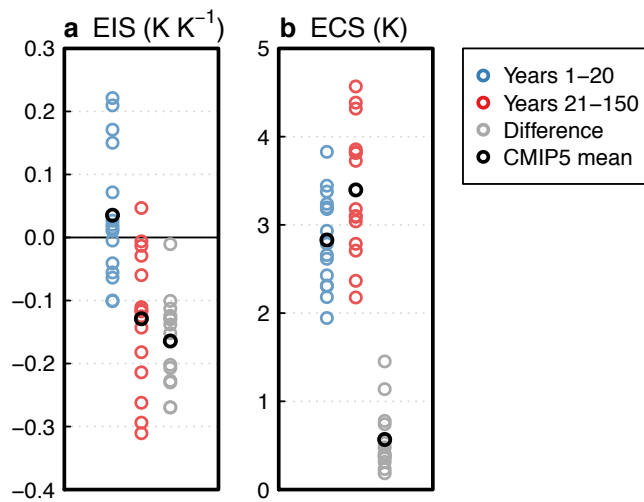
Model name	Planck	Lapse rate	RH	Albedo	Cloud	LW cloud	SW cloud	Total	Residual
ACCESS1.0	-1.84 (-1.85)	-0.26 (-0.01)	-0.01 (-0.01)	0.37 (0.59)	0.41 (0.48)	0.63 (0.31)	-0.22 (0.17)	-1.33 (-0.80)	0.25 (0.23)
<b>ACCESS1.3</b>	-1.85 (-1.85)	-0.18 (-0.03)	-0.10 (-0.02)	0.50 (0.54)	0.37 (0.78)	0.27 (0.16)	0.10 (0.62)	-1.27 (-0.59)	0.10 (0.10)
<b>BCC-CSM1.1</b>	-1.87 (-1.87)	-0.12 (0.11)	-0.07 (-0.06)	0.41 (0.64)	0.20 (0.28)	0.54 (0.36)	-0.34 (-0.08)	-1.44 (-0.89)	0.09 (0.03)
<b>BCC-CSM1.1(m)</b>	-1.86 (-1.87)	-0.14 (0.06)	-0.12 (-0.07)	0.45 (0.55)	0.27 (0.45)	0.27 (0.45)	-0.00 (-0.00)	-1.40 (-0.88)	0.03 (0.01)
BNU-ESM	-1.87 (-1.85)	-0.04 (0.03)	0.01 (0.07)	0.64 (0.65)	0.17 (-0.08)	0.47 (0.36)	-0.31 (-0.44)	-1.08 (-1.19)	0.12 (0.06)
<b>CanESM2</b>	-1.86 (-1.85)	-0.22 (-0.07)	0.03 (-0.00)	0.38 (0.46)	0.52 (0.49)	0.90 (0.69)	-0.38 (-0.20)	-1.15 (-0.98)	-0.05 (0.08)
<b>CCSM4</b>	-1.85 (-1.87)	-0.12 (0.12)	-0.04 (-0.01)	0.51 (0.64)	-0.02 (0.28)	0.44 (0.28)	-0.46 (0.01)	-1.51 (-0.84)	-0.05 (-0.07)
CNRM-CM5	-1.86 (-1.85)	0.00 (-0.12)	-0.01 (-0.10)	0.67 (0.42)	0.13 (0.17)	0.40 (0.27)	-0.27 (-0.09)	-1.08 (-1.47)	0.03 (0.24)
FGOALS-s2	-1.87 (-1.87)	-0.10 (-0.06)	0.06 (0.06)	0.50 (0.69)	0.02 (0.03)	0.34 (0.53)	-0.32 (-0.50)	-1.39 (-1.15)	0.48 (0.41)
<b>GFDL-CM3</b>	-1.84 (-1.85)	-0.30 (-0.12)	-0.15 (-0.13)	0.44 (0.45)	0.73 (0.96)	0.45 (0.27)	0.28 (0.69)	-1.12 (-0.69)	-0.01 (0.09)
GFDL-ESM2G	-1.84 (-1.84)	-0.34 (-0.07)	0.08 (0.02)	0.25 (0.47)	-0.09 (0.60)	0.92 (0.34)	-1.01 (0.26)	-1.93 (-0.83)	0.36 (0.10)
GFDL-ESM2M	-1.83 (-1.83)	-0.33 (-0.12)	0.01 (0.02)	0.38 (0.40)	0.07 (0.28)	0.88 (0.26)	-0.80 (0.03)	-1.70 (-1.25)	0.34 (0.12)
<b>GISS-E2-H</b>	-1.85 (-1.85)	-0.18 (0.02)	0.11 (0.19)	0.40 (0.38)	-0.22 (-0.07)	0.66 (0.62)	-0.88 (-0.69)	-1.74 (-1.33)	-0.16 (-0.14)
GISS-E2-R	-1.84 (-1.86)	-0.35 (0.04)	0.15 (0.26)	0.32 (0.33)	-0.43 (0.05)	0.80 (0.63)	-1.23 (-0.58)	-2.14 (-1.19)	-0.24 (-0.14)
HadGEM2-ES	-1.85 (-1.85)	-0.14 (-0.04)	-0.00 (0.03)	0.47 (0.52)	0.34 (0.81)	0.59 (0.41)	-0.24 (0.40)	-1.18 (-0.52)	0.37 (0.18)
<b>INMCM4</b>	-1.87 (-1.84)	-0.05 (-0.13)	-0.05 (0.18)	0.53 (0.29)	-0.05 (0.42)	0.27 (0.49)	-0.32 (-0.07)	-1.49 (-1.07)	-0.17 (-0.15)
<b>IPSL-CM5A-LR</b>	-1.84 (-1.84)	-0.28 (-0.23)	-0.04 (0.00)	0.33 (0.35)	1.08 (1.22)	0.51 (0.58)	0.57 (0.64)	-0.76 (-0.50)	-0.11 (-0.08)
<b>IPSL-CM5B-LR</b>	-1.85 (-1.85)	-0.12 (-0.04)	-0.03 (0.03)	0.40 (0.36)	0.39 (0.74)	0.16 (0.48)	0.24 (0.26)	-1.20 (-0.76)	-0.00 (-0.03)
MIROC-ESM	-1.85 (-1.84)	-0.20 (-0.31)	-0.05 (-0.15)	0.71 (0.40)	0.28 (1.19)	0.65 (0.24)	-0.37 (0.96)	-1.10 (-0.70)	0.04 (0.06)
MIROC5	-1.86 (-1.83)	-0.21 (-0.17)	-0.07 (-0.00)	0.47 (0.59)	-0.08 (0.08)	0.26 (0.48)	-0.34 (-0.40)	-1.76 (-1.34)	0.03 (0.14)
<b>MPI-ESM-LR</b>	-1.85 (-1.84)	-0.27 (-0.18)	-0.15 (-0.07)	0.41 (0.58)	0.43 (0.54)	0.57 (0.70)	-0.14 (-0.16)	-1.43 (-0.98)	0.10 (0.07)
<b>MPI-ESM-MR</b>	-1.85 (-1.85)	-0.24 (-0.12)	-0.14 (-0.06)	0.41 (0.65)	0.33 (0.53)	0.48 (0.61)	-0.15 (-0.08)	-1.49 (-0.85)	0.09 (0.03)
<b>MPI-ESM-P</b>	-1.85 (-1.85)	-0.35 (-0.14)	-0.12 (-0.07)	0.27 (0.57)	0.43 (0.48)	0.63 (0.65)	-0.20 (-0.17)	-1.62 (-1.00)	0.12 (0.08)
<b>MRI-CGCM3</b>	-1.86 (-1.84)	-0.17 (-0.06)	-0.10 (-0.06)	0.37 (0.52)	0.28 (0.36)	0.02 (-0.06)	0.26 (0.42)	-1.48 (-1.07)	-0.06 (0.01)
<b>NorESM1-M</b>	-1.86 (-1.87)	-0.14 (0.07)	-0.00 (0.03)	0.40 (0.61)	-0.05 (0.35)	0.32 (0.28)	-0.37 (0.06)	-1.66 (-0.81)	0.02 (-0.02)
Mean (15 models)	-1.85 (-1.85)	-0.19 (-0.05)	-0.06 (-0.01)	0.41 (0.51)	0.31 (0.52)	0.43 (0.44)	-0.12 (0.08)	-1.38 (-0.88)	-0.00 (0.00)
Mean (all models)	-1.85 (-1.85)	-0.19 (-0.06)	-0.03 (0.00)	0.44 (0.51)	0.22 (0.46)	0.50 (0.41)	-0.28 (0.04)	-1.42 (-0.95)	0.07 (0.06)

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**Fig. S1.** Multi-model mean normalized changes in SST and EIS during years 1–20 (a,b) and 21–150 (c,d), calculated by regressing annual-mean SST and EIS against global-mean temperature during the respective periods. Numbers in the top left corner of each panel denote global-mean values.

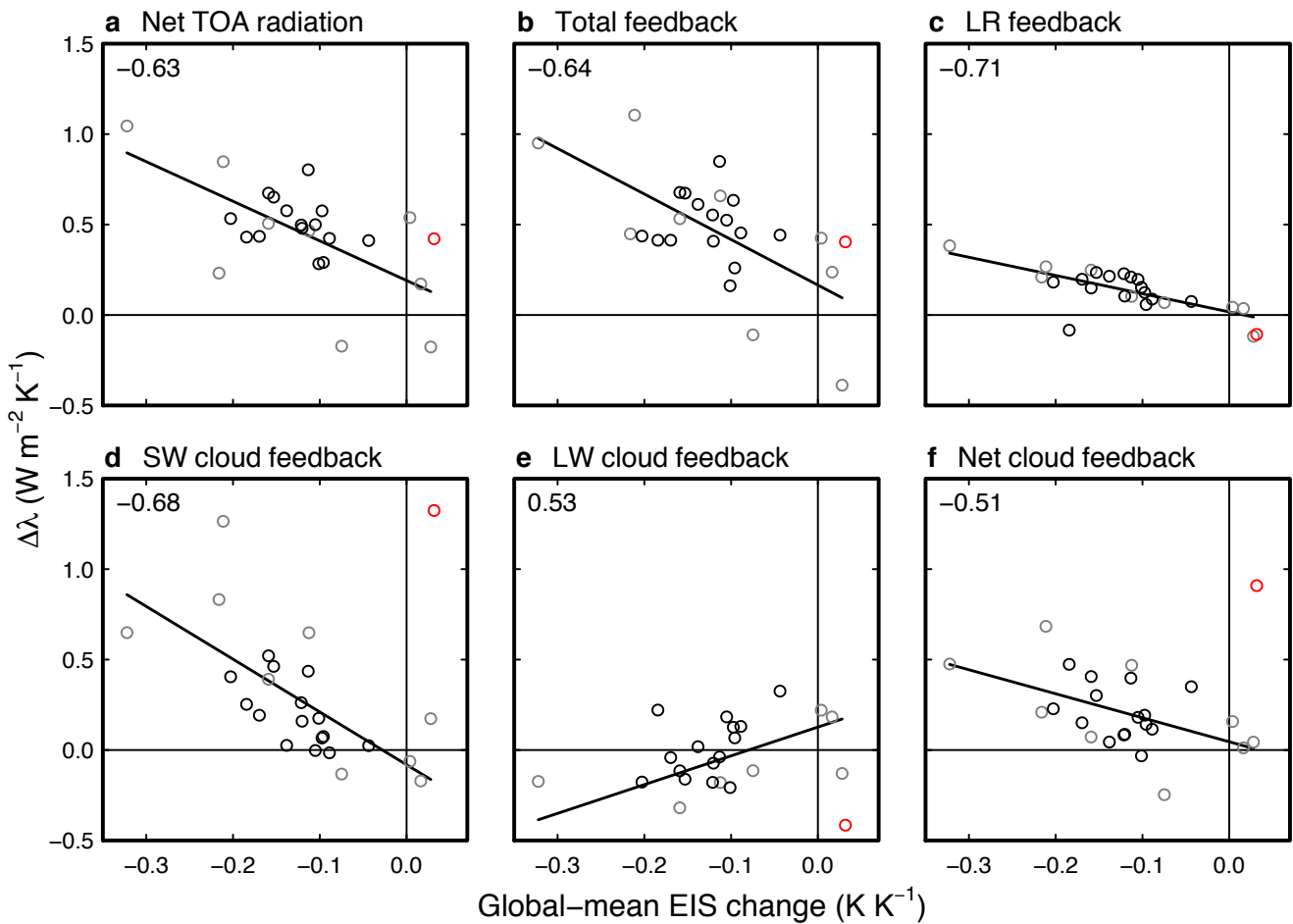
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**Fig. S2.** Changes in annual-mean global-mean EIS (a) and ECS (b) during years 1–20 (blue), years 21–150 (red), and the difference between the two periods (gray). Each colored circle represents a model, and black circles denote multi-model means. EIS changes are calculated by regressing global-mean EIS onto global-mean temperature during each period. See the Materials and Methods section for the ECS calculation.

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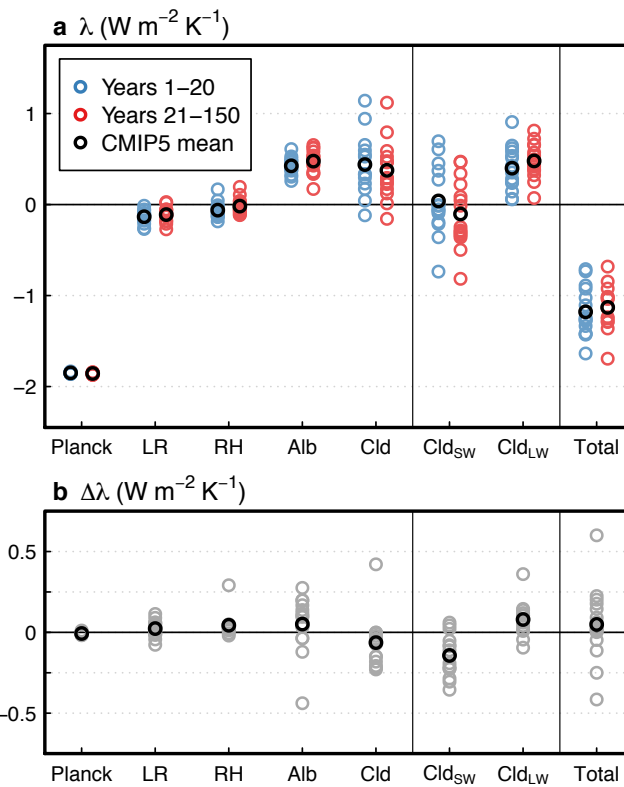
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**Fig. S3.** Change in feedback parameter versus change in global-mean EIS response per unit warming. Shown are changes in (a) net feedback based on TOA radiation, (b) the sum of kernel-derived feedbacks, (c) lapse rate feedback, (d)–(f) shortwave, longwave, and net cloud feedback. The changes are calculated as late (years 21–150) minus early (1–20) period. Black lines denote ordinary least-squares regression slopes. Black circles denote the 15 models used in the analysis; the red circle represents an outlier model, MIROC-ESM, excluded from the calculation of the regression slopes and correlation coefficients (Text S1); and gray circles represent the remaining 9 models (Table S1). The correlation coefficients are calculated for all models, minus MIROC-ESM. Note that regions poleward of 50° are excluded from the global-mean EIS calculation (Materials and Methods).

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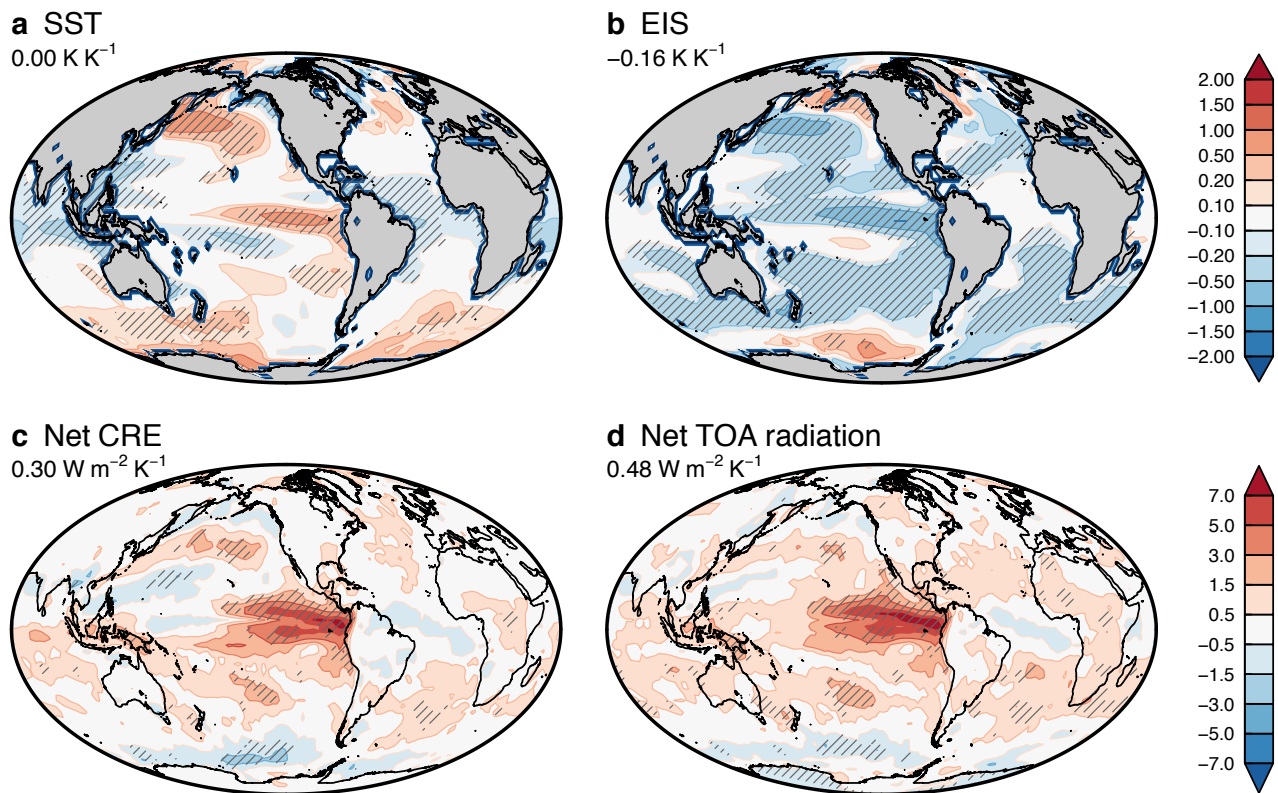
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**Fig. S4.** As in Fig. 2 but showing feedback values calculated following the local feedback perspective of Armour et al. (7). See Text S3 for details of the calculation method.

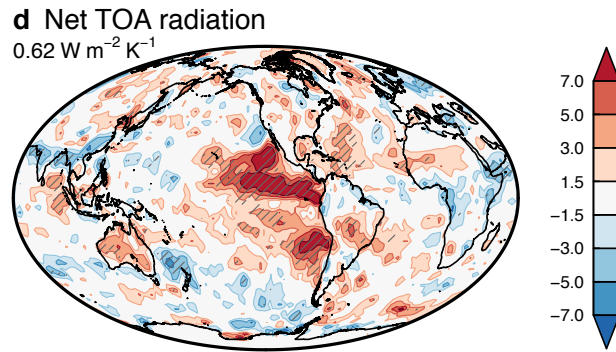
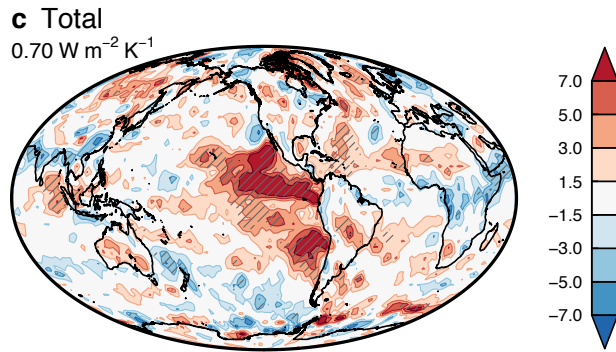
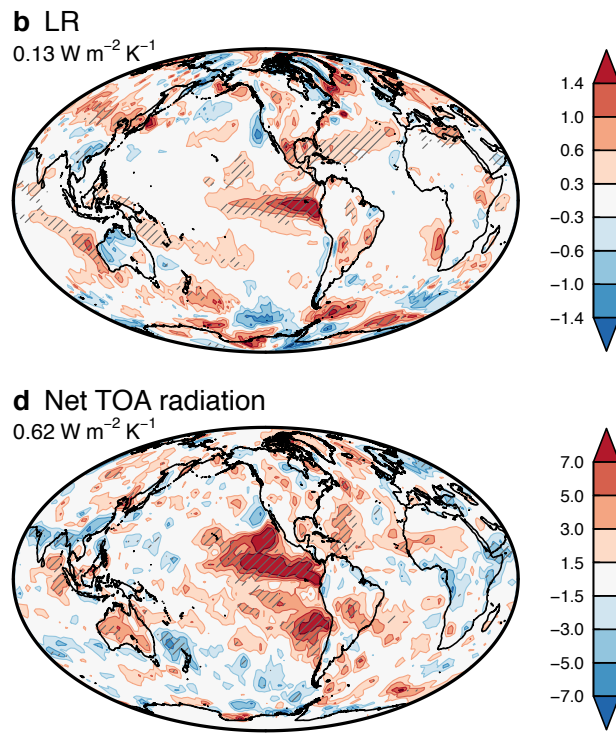
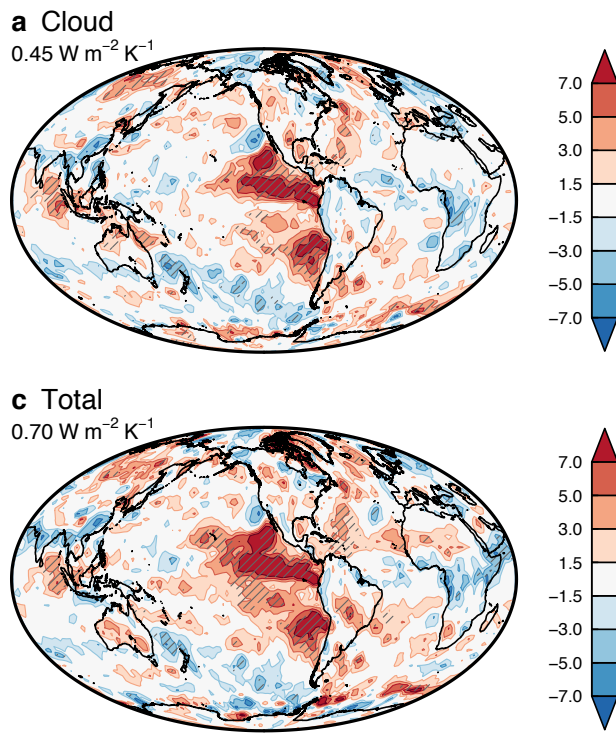
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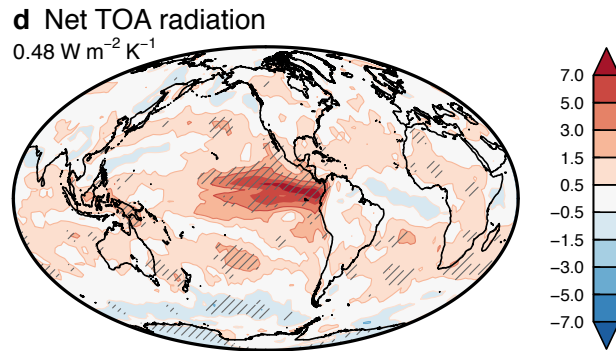
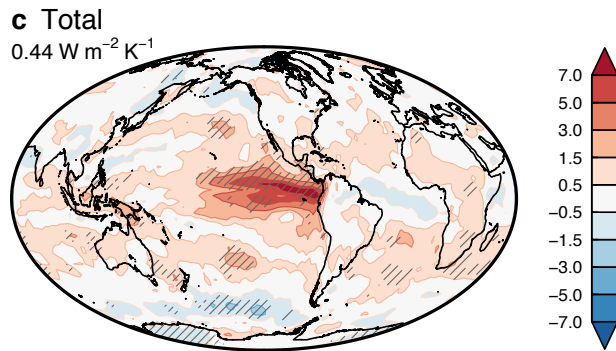
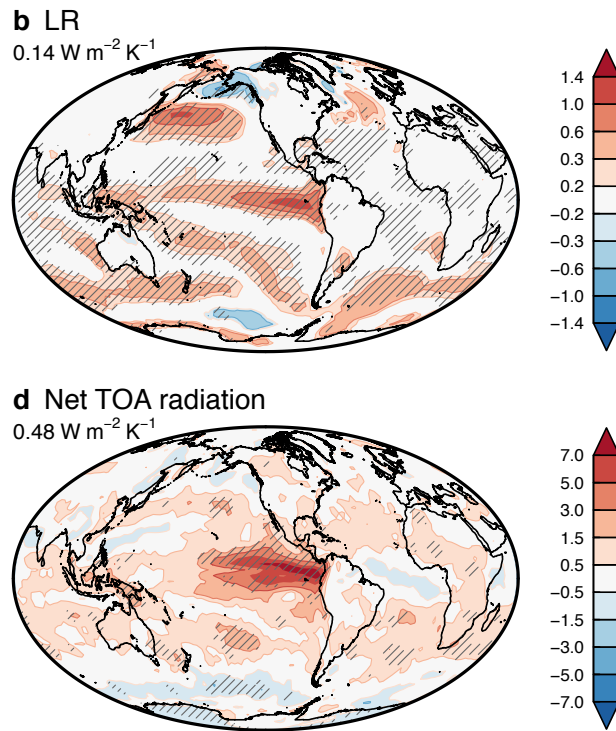
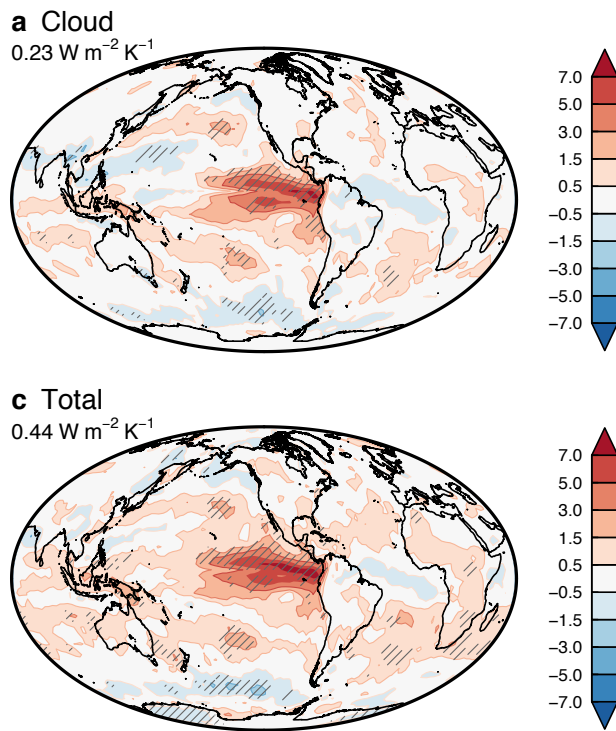
**Fig. S5.** As in Fig. 4, but using pre-industrial control data in the 15 models used in the analysis. Shown are the multi-model mean regression patterns, rescaled to yield anomalies consistent with a  $-0.16 \text{ K K}^{-1}$  global-mean EIS change to aid comparison with Figs. 1 and 3. Hatching denotes a multi-model mean anomaly larger than one standard deviation. Note that the effect of changes in global-mean surface temperature has been regressed out (Materials and Methods).

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**Fig. S6.** Contributions to stability-induced top-of-atmosphere radiative anomalies in observations by (a) clouds, (b) lapse rate changes, and (c) the sum of all the components (Planck, lapse rate, water vapor, surface albedo, and clouds). Panel (d) shows the actual net radiative anomalies (as in Fig. 4d) for comparison with (c). The radiative anomaly decomposition in (a)–(c) was calculated with radiative kernels (Materials and Methods). All the anomalies are scaled for a  $-0.16 \text{ K K}^{-1}$  change in global-mean EIS for comparison with climate model results (cf. main text and Fig. 4). Hatching indicates a statistically significant regression coefficient at the 5% level.

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**Fig. S7.** As in Fig. S6, but for the interannual stability-induced radiative anomalies in climate models (cf. Fig. S5). Shading represents multi-model mean results, and hatching denotes a multi-model mean anomaly larger than one standard deviation across models.