

Evaluating Observational Constraints on Intermodel Spread in Cloud, Temperature and Humidity Feedbacks

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Key Points:

- Observed interannual variation provides a useful constraint to narrow the uncertainty in long-term cloud feedback.
- It is not possible to constrain the long-term LR+WV feedback uncertainty with available observations of interannual variability.
- Disagreements in the response of tropical relative humidity are responsible for the long-term clear-sky LR+WV feedback spread.

Abstract

Uncertainty in climate feedbacks is the primary source of the spread in projected surface temperature responses to anthropogenic forcing. Cloud feedback persistently appears as the main source of disagreement in future projections while the combined lapse-rate plus water vapor (LR+WV) feedback is a smaller (30%), but non-trivial source of uncertainty in climate sensitivity. Here we attempt to observationally constrain the feedbacks in an effort to reduce their intermodel uncertainties. The observed interannual variation provides a useful constraint on the long-term cloud feedback, as evidenced by the consistency of global-mean values and regional contributions to the intermodel spread on both interannual and long-term timescales. However, interannual variability does not serve to constrain the long-term LR+WV feedback spread, which we find is dominated by the varying tropical relative humidity (RH) response to interhemispheric warming differences under clear-sky conditions and the RH-fixed LR feedback under all-sky conditions.

Plain Language Summary

How much the Earth warms in response to greenhouse gas increases depends on the Earth's efficiency in restoring radiative equilibrium. This efficiency differs significantly among climate models due to differences in feedback processes, particularly the responses of clouds, temperature and water vapor to the initial perturbation. One approach to narrowing the intermodel spread of feedbacks is to only consider models whose observable variability is consistent with available measurements. The magnitude of cloud feedbacks on interannual and long-term timescales are closely related, which allows us to employ this approach with observational estimates of the interannual cloud feedback to constrain the long-term cloud feedback. However, this approach does not work for the feedback resulting from changes in the vertical distribution of temperature and water vapor (the combined lapse-rate plus water vapor feedback).

1 Introduction

The projected surface temperature responses to anthropogenic forcing have a large spread among global climate models, primarily due to large uncertainties in climate feedbacks (Flato et al., 2013). The cloud feedback has persistently been identified as the largest source of intermodel spread in effective climate sensitivity (ECS) across several generations of climate models (Dufresne & Bony, 2008; Vial et al., 2013; Zelinka et al., 2020). Although the cloud feedback appears positive in most models and thereby acts to amplify global warming, its magnitude differs substantially among models (Colman, 2003; Soden & Held, 2006; Soden et al., 2008; Zelinka et al., 2020). Accurately simulating clouds and their radiative responses has long been a stubborn challenge for climate modeling, largely because clouds depend on fine-scale physical processes that cannot be explicitly represented by coarse model grids. Although the representation of cloud processes have been improved in state-of-the-art climate models, including more accurate representation of supercooled liquid cloud water, the range of global-mean cloud feedback in the most recent generation of models has actually increased slightly (Bjordal et al., 2020; Zelinka et al., 2020).

Another important contributor to the uncertainty in ECS is the temperature feedback induced by tropospheric warming, which includes contributions from vertically uniform warming (Planck feedback) and departures from vertically uniform warming [lapse-rate (LR) feedback]. From a global-mean perspective, the latter constituent further leads to a large spread in the water vapor (WV) feedback, since atmospheric moistening responds via a nearly constant relative

humidity (RH) and thus follows the Clausius-Clapeyron relation (Soden & Held, 2006). Since these two components are tightly coupled in models, it is physically logical to analyze the LR+WV feedback instead of each term individually (Held & Soden, 2000). Even though there is cancellation between LR and WV feedbacks in both magnitude and intermodel spread, LR+WV feedback still possesses the second largest contribution (~30% that of cloud feedback) to the intermodel spread of ECS (Dufresne & Bony, 2008; Soden et al., 2008; Vial et al., 2013). Soden and Held (2006) noted that, individually, the global-mean LR and WV feedbacks are strongly related to the ratio of tropical to global-mean surface warming. Meanwhile, a recent study found that the global-mean RH-fixed LR feedback (the sum of LR feedback and its corresponding WV feedback component under RH-fixed condition; ~~the~~ Δ feedback) is largely driven by local model differences over southern extratropics (Po-Chedley et al., 2018), highlighting the role of Southern Ocean heat uptake in determining the global-mean LR+WV feedback, by partitioning of surface warming between tropics and southern extratropics.

Here we reexamine the sources of intermodel spread in cloud and LR+WV feedbacks across climate models from Coupled Model Intercomparison Project Phase 6 (CMIP6; Eyring et al., 2016), using a local feedback definition with global-mean surface temperature anomalies. We find the global-mean clear-sky LR+WV feedback uncertainty largely comes from the tropics, where local relative humidity response exhibits the largest intermodel disagreement. Meanwhile, the ~~the~~ Δ feedback is the largest contributor to all-sky LR+WV feedback uncertainty. We find this contribution largely occurs over northern extratropics, instead of southern extratropics reported in CMIP5 analysis by Po-Chedley et al. (2018) using a local feedback parameter estimated with local surface temperature anomalies. Additionally, we extend the well-established emergent constraint method (e.g., Klein & Hall, 2015) to these long-standing climate feedback challenges to investigate its utility in narrowing the spread of these feedbacks, in an effort to ultimately refine the estimate of ECS.

2 Data and Methodology

Climate feedbacks represent the amplification or dampening of radiative flux anomalies to internal variability or externally forced changes in global-mean surface temperature. Using observationally based radiative kernels derived from CloudSat/CALIPSO data (Kramer et al., 2019), we decompose top-of-atmosphere radiative flux anomalies into radiation changes caused by variations in temperature, water vapor, surface albedo and cloud, following Soden et al. (2008). Here, cloud radiative response, which is the sum of its longwave and shortwave components, is diagnosed from change in cloud radiative effect corrected for cloud masking effects on non-cloud radiative responses. Based on documented relationships between longwave and shortwave components for different cloud types (Webb et al., 2006), we further separate the cloud radiative responses into contributions from high, low and mixed clouds, following Soden and Vecchi (2011). The LR+WV radiative response is the sum of LR and WV radiative responses. Since differences in cloud climatologies can influence analyses of the all-sky LR+WV feedback, we focus primarily on uncertainties in the clear-sky LR+WV feedback in the main text, while further details of the all-sky LR+WV feedback are provided in the supplemental material (Text S1).

Climate models with the r1i1p1f1 realization available for both pre-industrial control (piControl) and abrupt quadrupling CO₂ (abrupt-4xCO₂) experiments are evaluated in this work (Table S1). Following Dessler (2013), interannual climate feedbacks are calculated as the linear regression slope of monthly deseasonalized global-mean radiative flux anomalies against

corresponding global-mean surface (air) temperature anomalies from piControl runs. To obtain the interannual climate feedbacks as accurately as possible, the longest simulation length available for all models (200 years) is used. Climate feedbacks in response to long-term climate change are calculated as the linear regression slope of annual global-mean radiative flux anomalies against corresponding global-mean surface temperature anomalies from standard 150-year abrupt-4xCO₂ experiments. Although the time-invariant feedback assumption adopted here is undermined by evolving pattern effects (e.g., Andrews et al., 2015; Chung & Soden, 2015; Andrews & Webb, 2018; Dong et al. 2020), the assumption is still useful for investigating the intermodel spread, for instance, since no noticeable difference occurs between the spread of cloud feedbacks derived from regressions over years 1–150 and years 21–150 of CMIP5 abrupt-4xCO₂ simulations (e.g., Zhou et al., 2015).

To evaluate the model-simulated global-mean feedbacks, observation-based interannual emergent constraints are adopted. The observed interannual feedbacks are calculated using radiative fluxes from CERES EBAF Edition 4.1 product (Loeb et al., 2018a, 2019), vertical profiles of temperature and humidity from ERA5 (Hersbach et al., 2020) and surface temperature from GISTEMP v4 (Lenssen et al., 2019). The corresponding 95% confidence intervals are calculated using standard deviations of the observed interannual feedbacks (i.e., linear regression slope) to provide observed uncertainty bounds. In addition, vertical profiles from Version 6 Level 3 AIRS retrievals (Aumann et al., 2003) and MERRA-2 reanalysis (Gelaro et al., 2017) are adopted for potential cross-validations. Because of the limited length of satellite observations, the observation-based estimates without (with) AIRS retrievals are conducted over the period of 2001 (2003) through 2019. To increase the credibility of the emergent constraints, we also evaluate whether these constraints work with the interannual feedback obtained from the same-period historical simulations. Since the historical simulations include period 2015–2019 from idealized 21st century scenario SSP2-4.5 (O'Neill et al., 2016) and are available for less models (Table S2), we present the interannual feedbacks from piControl runs for most of the manuscript.

3 Results

3.1 Emergent constraints

The emergent constraint method has been applied to help reduce the persistent intermodel spread of climate feedbacks (e.g., Hall & Qu, 2006; Qu & Hall, 2014). One key principle of the emergent constraint idea is that models failing to reproduce observed characteristics in unforced or historical simulations should not be trusted for future climate projections, especially if that characteristic in question is physically and statistically related across interannual and centennial timescales (Klein & Hall, 2015). Here, comparisons between global-mean interannual and long-term feedbacks are conducted (Figure 1). As shown in Figure 1a, there is a strong correlation ($r = 0.83$) between interannual and long-term cloud feedbacks. With a least-squares regression slope close to one (0.81 ± 0.17), the intermodel spread of cloud feedback is comparable on these timescales, which differs from previous findings using CMIP5-era models (Zhou et al., 2015; Colman & Hanson, 2017). For instance, Zhou et al. (2015) found the global-mean long-term cloud feedbacks of CMIP5-era models are generally smaller than their interannual counterparts, especially for those models with relatively large interannual feedback. This leads to a smaller regression slope (0.50). A slight increase in the long-term cloud feedback (Zelinka et al., 2020) and a decrease in the interannual cloud feedback, on average, in CMIP6-era models, are the causes for the larger regression slope found here.

Since the global-mean long-term and interannual cloud feedbacks are closely related in both magnitude and intermodel spread, it is possible to observationally constrain the former by identifying models with interannual cloud feedbacks that fall within observed uncertainty. In this case, we find the models with small or negative cloud feedback are inconsistent with observed uncertainty estimates (Figure 1a). Compared to Zhou et al. (2015), the narrower uncertainty range could be attributed to the longer observations, which captured a shortwave absorption increase during post-hiatus years, associated with decreases in low cloud cover (Loeb et al., 2018b). If one only considers models that are consistent with observations (i.e., dots fall within shading), the intermodel spread of long-term cloud feedback could be narrowed by approximately one-third (0.55 out of 1.63 $Wm^{-1}K^{-1}$). Since the ECS of a model is tied to the strength of its cloud feedback (e.g., Zelinka et al., 2020), our findings suggest a low ECS is unlikely, consistent with conclusions by Sherwood et al. (2020). However, a recent work by Wang et al. (2021), using an emergent constraint based on historical warming patterns, suggests low ECS models cannot be ruled out.

Figure 1b compares interannual and long-term clear-sky LR+WV feedbacks. Although the correlation between global-mean interannual and long-term clear-sky LR+WV feedbacks is statistically significant at the 99% level, observed interannual variation does not serve to constrain the long-term clear-sky LR+WV feedback spread. This is due to two reasons. First, the spread of long-term clear-sky LR+WV feedback (1.32–1.67 $Wm^{-1}K^{-1}$) is only half of that of interannual feedback (1.07–1.80 $Wm^{-1}K^{-1}$). Second, the observational-interannual uncertainty is nearly equal to the intermodel spread. Additionally, the observed interannual clear-sky LR+WV feedbacks differ considerably among different observational and reanalyses products, reflecting the large degree of uncertainty in available observations of temperature and humidity profiles (Kramer et al., 2021). Similar results are seen in all-sky LR+WV feedback (Figure S1), with a weaker correlation between global-mean interannual and long-term all-sky LR+WV feedback. Since the impact of profile uncertainties on cloud feedback is confined to the cloud masking effect, which is the secondary contribution to cloud radiative response, the observational uncertainties do not cause noticeable differences in the observed cloud feedback estimations. When we test these constraints using the CERES observational period from historical simulations, we find these constraints exhibit slightly weaker but consistently constraining effects on the intermodel spreads (Figure S2).

Surprisingly, the spread of tropical-mean long-term clear-sky LR+WV (1.61–2.37 $Wm^{-1}K^{-1}$) is twice as large as the global-mean spread. This is counter-intuitive. Since the tropical atmosphere has long been known for following well-documented processes (i.e., moist adiabatic lapse-rate and radiative-convective equilibrium; e.g., Santer et al., 2005), one might expect the spread of tropical-mean LR+WV feedback to be smaller than the global-mean spread. This motivates us to further explore the sources of intermodel spread in these feedbacks.

3.2 Intermodel spread analyses

To quantify local contribution of feedbacks and warming pattern to the global-mean intermodel feedback spread, a simple linear regression method is adopted, taking local feedback for example:

$$FB_{\text{local}} = aFB_{\text{global}} + b \quad (1)$$

Here, FB_{local} is the intermodel variation of local feedbacks, which is resolved at each grid point. The interannual (long-term) FB_{global} from each model is calculated by regressing monthly

deseasonalized (annual) local radiative response against corresponding global-mean surface temperature anomalies. FB_{spread} is the intermodel variation of global-mean feedbacks, which is the same for each grid. The “a” is the contribution from local intermodel uncertainty to the global-mean feedback spread. When FB_{spread} is large and varies with FB_{spread} , we can obtain a large value of “a”, suggesting a large contribution from local difference to the global-mean spread. The spatial distribution of this contribution will be referred to as “contribution pattern” hereafter. The “b” is the y-intercept of the linear regression, a meaningless parameter in this method.

Figures 2a-b highlight the contribution from local cloud feedback differences to the spread in global-mean cloud feedback. The contribution patterns for interannual and long-term cloud feedbacks exhibit similar characteristics. Specifically, local feedback differences over eastern Pacific and Southern Ocean contribute the most to the global-mean cloud feedback spread on both timescales. Additionally, most of regions with statistically significant contribution to the global-mean cloud feedback spread are associated with low clouds (Figure S3c-d). This supports the utility of the observed constraint on global-mean long-term cloud feedback, since an emergent constraint must be based on a coherent relationship between intermodel variations in an observable quantity and in its future projection (Klein & Hall, 2015). This consistency between interannual and long-term contribution patterns is also evident in both shortwave and longwave cloud feedbacks (Figure 2c-f), although the magnitude of local contribution on long-term timescales is generally smaller than that on interannual timescales. As expected, the shortwave component dominates local contributions to global-mean, total cloud feedback (Figure 2a-d & S3a-d), given the considerable importance of low cloud feedback.

A similar analysis is applied to the LR+WV feedback (Figure 3a-b & S4a-b). Generally, the spread of global-mean LR+WV feedback is driven by feedbacks over tropics on both interannual and long-term timescales, except the long-term all-sky LR+WV feedback is dominated by the northern extratropics (Figure S5). However, the contribution patterns are noticeably different on these timescales. For instance, the intermodel spread of long-term LR+WV feedback is driven by an interhemispheric asymmetric contribution pattern which is not observed on interannual timescales. This difference highlights the challenge in using observed variability to constrain global-mean long-term LR+WV feedback, since the difference suggests that the physical processes that shape these feedbacks are timescale dependent.

Interestingly, the spread in global-mean long-term clear-sky LR+WV feedback is partly reduced due to compensation between northern and southern extratropics (Figure 3b & S5b-d), with a correlation of -0.74 between corresponding regional average of local feedbacks. Even though there is also substantial hemispheric cancellation in the tropics, a regional-mean regression coefficient of 1.40 presents over tropics. This explains why the spread of global-mean long-term clear-sky LR+WV feedback is considerably smaller than that of interannual counterpart, and why the spread of tropical-mean long-term clear-sky LR+WV feedback is twice as large as that of global-mean feedback.

Following Held and Shell (2012), we further decompose the LR+WV feedback into WV feedback caused by the vertical-uniform warming under RH-fixed condition (WV_{uniform} feedback), ΔR feedback and RH feedback, as following:

$$LR + WV = WV_{\text{uniform}} + \Delta R + RH \quad (2)$$

The contribution of local uncertainty to the spread of global-mean LR+WV feedbacks are shown for each component (Figure 3c-h & S4c-h). The decomposition reveals that the large uncertainties in tropical LR+WV feedback comes from intermodel uncertainties in the RH feedback (e.g., Figure 3a-b & 3g-h). In particular, the spread of global-mean clear-sky feedback is dominated by differences in the tropical RH feedback, with a correlation of 0.94 (0.98) between long-term, global-mean (tropical-mean) clear-sky LR+WV and RH feedbacks (Figure 3i). The high correlation over tropics is consistent with Vial et al. (2013) and Po-Chedley et al. (2018). For the same reasons mentioned in section 3.1 regarding the LR+WV feedback, the RH feedback also cannot be constrained with observations (Figure 3j & S7).

The local, offsetting extratropical contributions to the global-mean long-term clear-sky LR+WV feedback spread mostly come from local uncertainties of the WV_{uniform} feedback (Figure 3b & 3d). The interhemispheric asymmetry of WV_{uniform} contribution pattern also partly reflects a meridional warming asymmetry. Meanwhile, signals are weak in the contribution pattern of clear-sky $\Delta\tau$ feedback (Figure 3e-f & S6b). Similar patterns of local contribution occur under all-sky conditions (Figure S4c-h), except for the enhanced $\Delta\tau$ feedback contribution, which correspondingly weakens the offsetting extratropical all-sky LR+WV feedback contributions (Figure S4b & S5f-h). The enhanced $\Delta\tau$ feedback contribution is because the sensitivity of radiative flux to upper-tropospheric temperature and humidity anomalies amplifies under all-sky conditions (e.g., Soden et al., 2008). Especially, there are noticeably larger positive contributions from local uncertainties of long-term all-sky $\Delta\tau$ feedback over northern extratropics (Figure S4f), compared to those under clear-sky conditions (Figure 3f). This is due to a negative covariation ($r = -0.57$) between warming extents over northern extratropics and tropics (Figure 3d & S4d). The negative covariation amplifies the all-sky $\Delta\tau$ feedback uncertainty over northern extratropics and its contribution to the global-mean all-sky LR+WV feedback spread (Text S1).

Our findings, in part, differ from the CMIP5 analyses by Po-Chedley et al. (2018). First, they showed that local feedback spread over southern extratropics drives the model variability in global-mean long-term all-sky $\Delta\tau$ feedback, while we find most of these uncertainties occur in northern extratropics across CMIP6-era models and contribute more to the global-mean all-sky LR+WV feedback spread. Additionally, the uncertainty in clear-sky LR+WV feedback largely comes from tropics (Figure 3a-b & 3g-h), where local relative humidity responses exhibit the largest intermodel disagreement. The corresponding RH feedback uncertainty also plays a secondary role in determining all-sky LR+WV feedback spread (Figure S6f). However, it should be noted that the local feedback calculation is different, as their calculations use local surface temperature anomalies instead of global-mean surface temperature anomalies and thus are more strongly influenced by local warming asymmetries (Feldl & Roe, 2013; Text S2).

The question then arises: Do differences in warming patterns modify these climate feedbacks? To answer this question, we extend our analysis to uncertainties in local surface temperature sensitivities, which is calculated by regressing time-evolving abrupt-4xCO₂ local surface temperature against global-mean surface temperature and will be referred to as “warming pattern” hereafter. By adopting the same analysis method [Eq. (1)] to warming patterns against the global-mean long-term feedbacks, we find the long-term cloud feedback spread has an interhemispheric-asymmetric dependence on the warming pattern uncertainty (Figure 4a). The positive contribution over southern extratropics is likely driven by low cloud thermodynamic and stability mechanisms affecting shortwave cloud feedback (Figure 2d & S3d; Klein & Hartmann, 1993; Wood & Bretherton, 2006; Bretherton, 2015; Qu et al., 2015), while the negative

contribution over north Pacific could be attributed to divergent low cloud responses to different jet shifts (Zelinka et al., 2018), which are determined by local warming gradient (Yang et al. 2002). In contrast, the spread of long-term LR+WV feedbacks is driven by an opposite meridional asymmetry (Figure 4b, S8b, S9c & S9f). This is consistent with the above-mentioned uncertainty contribution pattern of the WV_{uniform} feedback. The most noticeable contribution occurs over Southern Ocean (Figure 4b), where uncertainty in ocean heat uptake plays an essential role in manipulating the regional warming extent, as shown in Po-Chedley et al. (2018). Decomposing the LR+WV feedback further, we find warming pattern uncertainty modifies the overall LR+WV feedback largely via its effect on the RH feedback (Figure S8a-b & S8g-h). Its effect on the all-sky ΔR feedback also contribute to the LR+WV feedback spread, although there is a cancellation between its effect on WV_{uniform} and ΔR feedbacks, caused by the opposite contribution from tropical warming extent (Figure S8a-f; Soden and Held, 2006). Finally, we note that the opposite dependences of cloud and LR+WV feedbacks on warming patterns ultimately lead to a statistically significant negative correlation between these two feedbacks (Caldwell et al., 2016). It mostly comes from the negative correlation between cloud and RH feedbacks (Figure S10).

4 Conclusions and discussion

Here we attempt to observationally constrain the long-term cloud and LR+WV feedbacks in an effort to reduce their intermodel uncertainties. The results indicate that observed interannual variation provides a useful constraint to narrow the uncertainty in global-mean long-term cloud feedback. Similar regional uncertainty contributions on both interannual and long-term timescales reflect a consistent behavior of low cloud changes and bolster the effectiveness of the observed constraint. In contrast, the long-term LR+WV feedback cannot be constrained with observations of interannual variability. This arises for two reasons: i) the spread of global-mean long-term LR+WV feedback is only half as large as that of interannual feedback; and ii) the observed uncertainty from individual observation nearly equals to the intermodel spread of global-mean interannual LR+WV feedback. Additionally, there is a large discrepancy among different observations and reanalyses products on the value of interannual LR+WV feedback. The spread of global-mean long-term clear-sky LR+WV feedback is largely determined by the tropics, where the largest contribution comes from the uncertainties in the local RH feedback, with a remarkably high correlation between clear-sky LR+WV and RH feedbacks. The RH feedback spread, which also plays a secondary role in determining all-sky LR+WV feedback spread, is shown to be associated with model differences in interhemispheric warming asymmetry, induced primarily by Southern Ocean heat uptake differences. Meanwhile, the all-sky ΔR feedback uncertainty, which is larger than its counterpart under clear-sky conditions, largely determines the global-mean long-term all-sky LR+WV feedback spread and is substantially caused by the negative covariation between warming extents over northern extratropics and tropics.

While the pattern of local warming contribution to the global-mean long-term LR+WV feedback suggests Southern Ocean heat uptake plays a role in uncertainty, a direct connection is not immediately obvious. For example, less warming due to more Southern Ocean heat uptake should lead to a smaller local LR+WV feedback, not the larger global-mean LR+WV feedback as we find. Hence, Southern Ocean heat uptake likely exerts its impact on the global-mean LR+WV feedback in indirect ways, for instance by suppressing ocean heat uptake and leveraging a larger fraction of surface warming over northern extratropics via a weakened Atlantic meridional overturning circulation. This linkage is supported by a strong correlation of -0.84 between

warming extents over southern and northern extratropics, suggesting a robust heatsink seesaw between these regions. Hence, the warming pattern shows broadly consistent signal over southern extratropics, instead of dipole pattern related to subdued warming (Armour et al., 2016). The warming pattern difference could be further attributed to salinity differences, which are primarily induced by varying difference between precipitation and evaporation (e.g., Liu et al., 2020). Finally, the amplifying meridional warming asymmetry could lead to a shift in Intertropical Convergence Zone, thereby modifying the LR+WV feedback (Text S3).

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Competing Interests

Authors have no competing interests.

Data Availability Statement

The CMIP6 data are available at <https://esgf-node.llnl.gov/search/cmip6/>. The CMIP6 models used in this work are listed in Tables S1 and S2 in the supporting information file. The CERES radiative flux observations are available at <https://ceres.larc.nasa.gov/data/#ebaf-level-3>. The GISTEMP is available at <https://data.giss.nasa.gov/gistemp/>. The ERA5 reanalysis data are available at <https://cds.climate.copernicus.eu/cdsapp#!/dataset/reanalysis-era5-pressure-levels-monthly-means?tab=overview>. The AIRS temperature and water vapor observations and the MERRA-2 reanalysis data are available at https://disc.gsfc.nasa.gov/datasets/AIRS3STM_006/summary?keywords=AIRS and https://disc.gsfc.nasa.gov/datasets/M2IMNPASM_5.12.4/summary?keywords=MERRA2, respectively. The CloudSat/CALIPSO radiative kernels used in this study and related code for applying them are available at <https://climate.rsmas.miami.edu/data/radiative-kernels/>.

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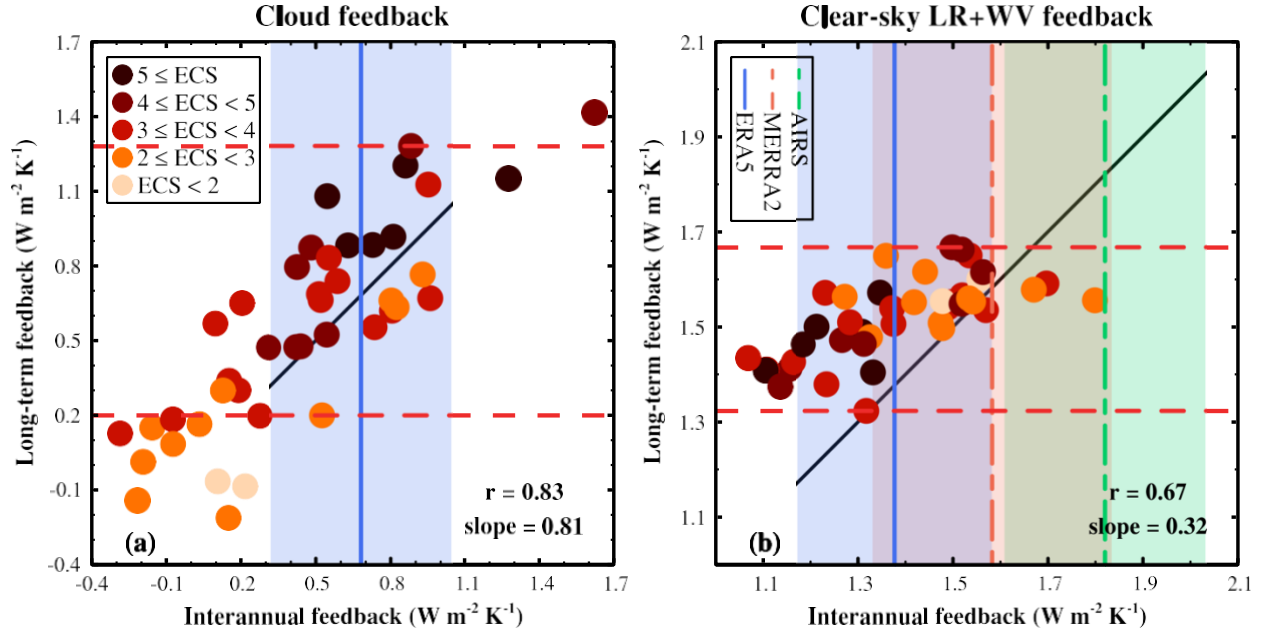


Figure 1. Scatterplots of global-mean interannual (a) cloud and (b) clear-sky LR+WV feedbacks versus their corresponding long-term feedbacks. The vertical lines denote observed interannual feedbacks, while the shadings show their corresponding 95% confidence intervals. The red horizontal dash lines highlight the spreads of long-term feedbacks constrained by the observed feedbacks using ERA5 vertical temperature and humidity profiles.

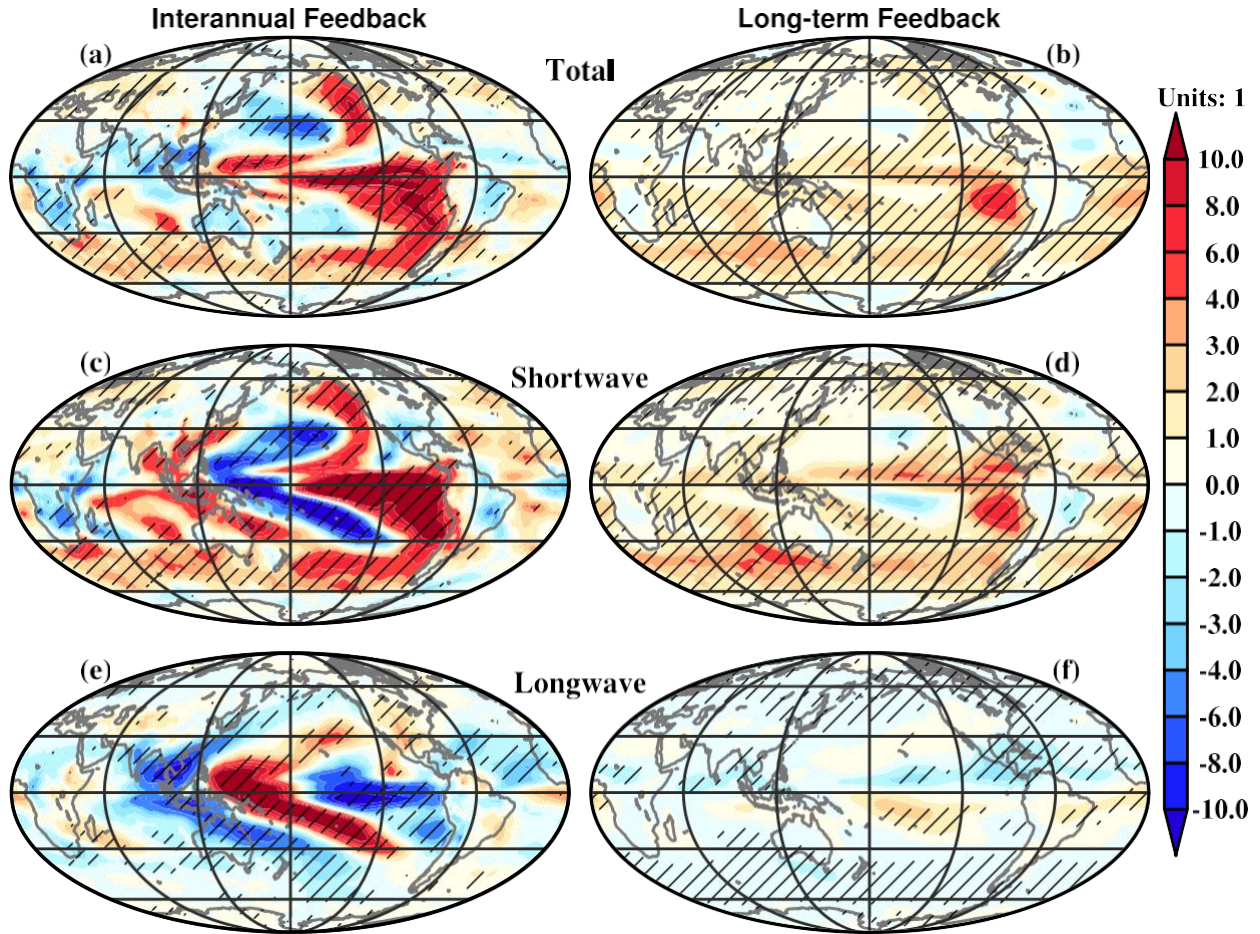


Figure 2. Cross-model regressions of local (a-b) total, (c-d) shortwave and (e-f) longwave cloud feedbacks against global-mean total cloud feedback on both (left) interannual and (right) long-term timescales. Hatching indicates area where regression is statistically significant at the 95% level.

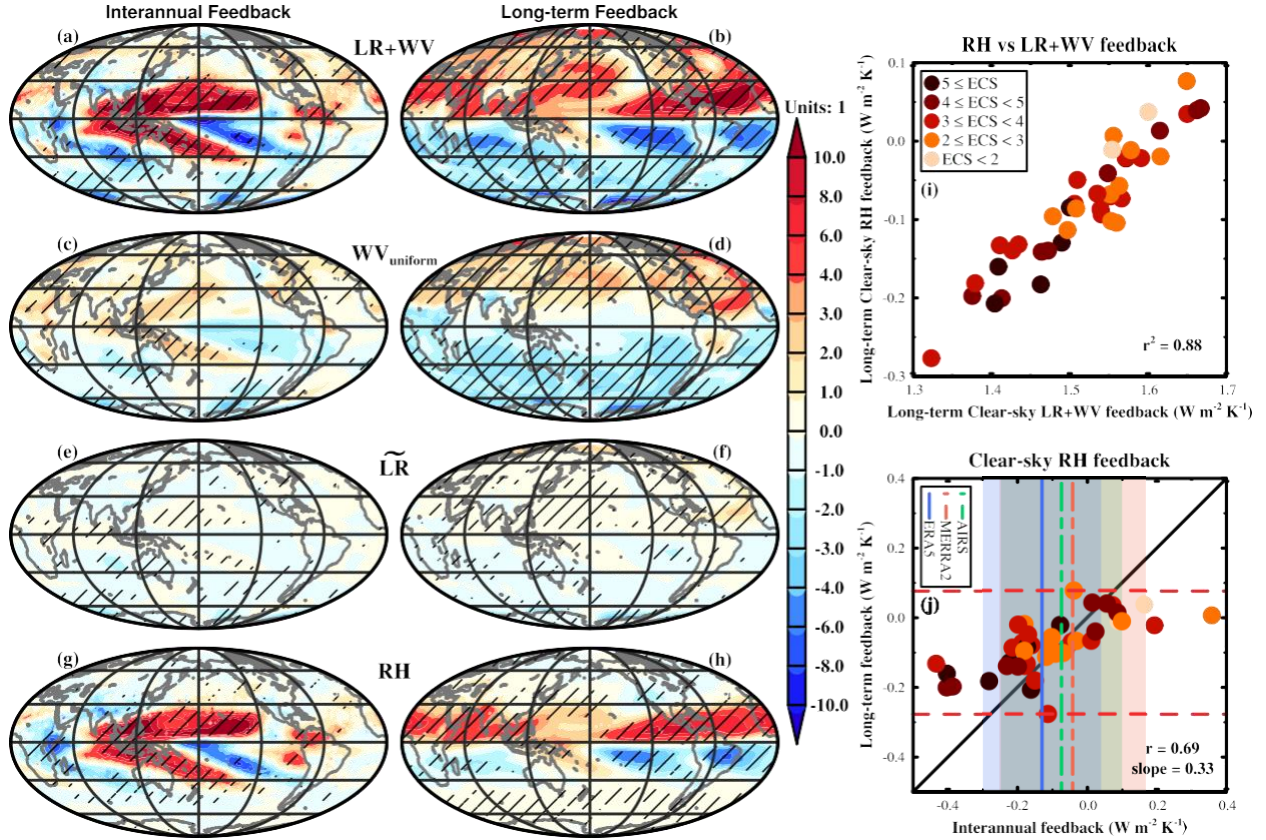


Figure 3. Cross-model regressions of local clear-sky (a-b) LR+WV, (c-d) WV_{uniform} , (e-f) $\tilde{LR}$ and (g-h) RH feedbacks against global-mean clear-sky LR+WV feedback on both (left) interannual and (middle) long-term timescales. Hatching indicates area where regression is statistically significant at the 95% level. (i) is a comparison between long-term clear-sky LR+WV and RH feedbacks, while (j) is same as Figure 1b except for clear-sky RH feedback.

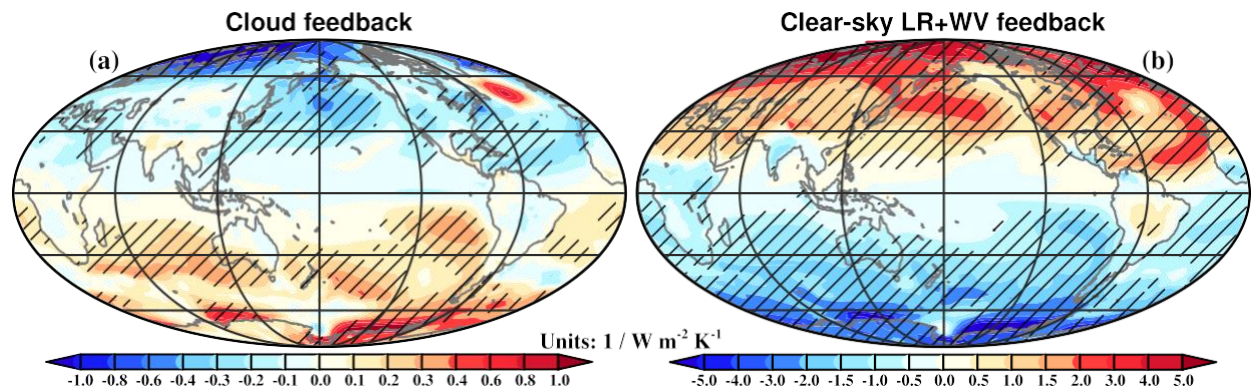


Figure 4. Cross-model regressions of local surface temperature sensitivity to global-mean long-term (a) cloud and (b) clear-sky LR+WV feedbacks. Hatching indicates area where regression is statistically significant at the 95% level.

Evaluating Observational Constraints on Intermodel Spread in Cloud, Temperature and Humidity Feedbacks

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Introduction

In this Supporting Information, we provide tables of CMIP6 models we used (Tables S1 and S2) and their global-mean values of feedbacks on both interannual (piControl) and long-term timescales (Tables S3 and S4), additional figures that support the results in the main text and supporting information (Figures S1-S13), Text S1 providing the details of the all-sky LR+WV feedback analyses, Text S2 discussing the differences raised by different local feedback calculations, and Text S3 offering a discussion on the potential causes of the RH feedback uncertainty.

26 **Text S1**

27 *Comparison between clear-sky and all-sky LR+WV feedbacks*

28 Although the main text focuses on the clear-sky LR+WV feedback, we provide a comparison
29 between clear-sky and all-sky LR+WV feedbacks here to show further details of the all-sky
30 LR+WV feedback. We do the similar contribution analyses of local feedback uncertainty to the
31 spread of global-mean all-sky LR+WV feedback for each component (Figure S4). Generally, the
32 contribution patterns are similar to those under clear-sky conditions (Figure 3a-h), except for the
33 enhanced $\tilde{R}$ feedback contribution (Figure 3e-f & S4e-f) and corresponding weakened offsetting
34 extratropical LR+WV feedback contribution (Figure S5f-h). As a result, the spread of global-mean
35 long-term all-sky LR+WV feedback is largely determined by the local feedback uncertainties over
36 the northern extratropics (Figure S5h), which mostly comes from the local $\tilde{R}$ feedback
37 uncertainties. The major difference presented in the contribution from $\tilde{R}$ feedback to the global-
38 mean clear-sky and all-sky LR+WV feedback spread is due to two reasons. First, the sensitivity of
39 radiative flux to upper-tropospheric temperature and water vapor anomalies amplifies under all-
40 sky conditions, which you can see in FIG. 1-2 of Soden et al. (2008) and Figure 4-5 of Kramer et
41 al. (2019). Second, most of LR profile uncertainty occurs over the upper troposphere, since the
42 lower troposphere is closely coupled with surface and thereafter the lower troposphere has less
43 temperature departure from vertical-uniform warming and correspondingly smaller intermodel
44 uncertainty than that of the upper troposphere. If one compares the contribution patterns of both
45 clear-sky and all-sky local $\tilde{R}$ feedback uncertainty to their corresponding LR+WV feedback
46 closely (Figure 3e-f & S4e-f), a difference could be noted between that on interannual and long-
47 term timescales. The enhancement from clear-sky to all-sky $\tilde{R}$ feedback contribution is globally
48 uniform on interannual timescales while the amplification on long-term timescale mostly locates

over northern extratropics. The latter one differs from the CMIP5 analyses by Po-Chedley et al. (2018), although we do show large $\tilde{R}$ feedback uncertainties over southern extratropics with their method (Figure S11d). However, the large $\tilde{R}$ feedback uncertainty over southern extratropics is more likely to suggest that the local uncertainty comes from surface warming difference instead of the difference in radiative flux anomalies, since we do not see significant $\tilde{R}$ feedback contribution over southern extratropics to the global-mean LR+WV feedback (Figure S4f). The explanation Po-Chedley et al. (2018) used to clarify CMIP5 small $\tilde{R}$ feedback uncertainty over northern extratropics works for CMIP6 small uncertainty over southern extratropics. An extremely weak, same-sign covariation ($r = 0.03$) between warming extents over tropics and southern extratropics could be seen in Figure S4d while there is a strong negative covariation ($r = -0.57$) between tropics and northern extratropics. Since the upper-tropospheric temperature over extratropics depends on the tropical surface warming (e.g., Po-Chedley et al., 2018), or more specifically on the warming of tropical warm pool, the opposite covariation between warming extents over tropics and northern extratropics leads to a large LR uncertainty and furtherly a large $\tilde{R}$ feedback uncertainty over northern extratropics while southern extratropics has a small $\tilde{R}$ feedback uncertainty. In this case, tropical warming extent (or the ratio of tropical to global-mean warming) show its effect on modulating all-sky LR+WV feedback (Figure S9e) via its effects on $\tilde{R}$ feedback (Figure S6e & S8f), although its effects on $WV_{uniform}$ feedback slightly undermine the contribution of $\tilde{R}$ feedback to LR+WV feedback spread (Figure S6d-e, S8d & S8f). Since there is a strong negative correlation ($r = -0.84$) between warming extents over northern and southern extratropics, which attenuates the intermodel uncertainty in extratropical warming extent, the ratio of tropical to extratropical surface warming has a similar relationship with global-mean all-sky LR+WV feedback as tropical warming extent has (Figure S9d-e).

72 Text S2

73 *Analyses of LR+WV feedback following Po-Chedley et al. (2018)*

74 Different from our definition of local feedback, Po-Chedley et al. (2018) defined local feedback
75 as the local (or area-average) radiative response resulting from a given feedback process divided
76 by the local (or area-average) surface temperature change, following the equation $\lambda = \frac{\Delta R}{\Delta T_s}$. There
77 are two key differences between the definitions of Po-Chedley et al. (2018) and ours. One is that
78 Po-Chedley et al. (2018) used local surface temperature instead of global-mean surface
79 temperature. The other is that Po-Chedley et al. (2018) used division of the average difference
80 between two states rather than regression of anomalies evolving over time.

81 Here, we reproduce their FIG. 3 using the annual average response for year 120-140 of CMIP6
82 abrupt-4xCO₂ experiments (Figure S11), as they did for CMIP5. Compared to FIG. 3 of Po-
83 Chedley et al. (2018), we can see similar model uncertainty distributions with substantial
84 uncertainty over the Southern Ocean or the subantarctic region, except that CMIP6 has a larger
85 uncertainty over the northern tropics for the WV, LR+WV and RH feedbacks (Figure S11b-c &
86 S11e). To a minor extent, this could contribute to differences between conclusions from Po-
87 Chedley et al. (2018) and ours.

88 We also quantify the contribution from local feedback uncertainty to global-mean LR+WV
89 feedback spread for results obtained from method of Po-Chedley et al. (2018), using Eq. (1) in
90 main text. Clearly, we cannot see the interhemispheric asymmetry in the results from their method
91 (Figure S12). It is an important evidence for us to explain why we could not constrain LR+WV
92 feedback with observations.

93 We can consider a situation with more warming over the northern hemisphere (NH) and less
94 warming over the southern hemisphere (SH) to understand why the different methods lead to
95 different results. This condition usually corresponds with a large LW+WV feedback from our
96 analyses (Figure 3d & S4d). In this case, we would get a large WV_{uniform} feedback over the NH
97 and a small WV_{uniform} feedback over the SH using global-mean surface temperature. However, if
98 we use local surface temperature, as in Po-Chedley et al. (2018), we will get comparable WV_{uniform}
99 feedbacks over both the NH and SH, since using local temperature in their method decreases
100 (increases) the WV_{uniform} feedback over the NH (SH) compared to results using global-mean
101 surface temperatures. More specifically, when the large (small) WV_{uniform} radiative response over
102 the NH (SH) is divided by local surface temperature that is larger (smaller) than global-mean
103 surface temperature, we would get a lower (higher) WV_{uniform} feedback compared to the one
104 calculated using global-mean surface temperature. In this case, the intermodel differences in local
105 feedbacks would be narrowed. As a result, we cannot see the interhemispheric asymmetry in
106 WV_{uniform} feedback contribution pattern using results obtained from method Po-Chedley et al.
107 (2018) used (Figure S12b). A similar logic also explains why using local surface temperature
108 results in a much-weakened interhemispheric asymmetry in the RH feedback contribution pattern
109 (Figure S12d). Additionally, using local surface temperature would amplify $\tilde{R}$ feedback over the
110 Southern Ocean and North Atlantic warming hole region (Figure S12c), especially when there has
111 more ocean heat uptake and lower surface temperature, although the noisily extreme value could
112 be removed by using zonal-mean surface temperature for local feedback calculation (Figure S13).
113 In this case, this method using local or zonal-mean surface temperature for local feedback
114 calculation would amplify the contributions from local $\tilde{R}$ feedback uncertainties over these
115 regions to global-mean LR+WV feedback spread.

116 Text S3

117 *Discussion: what causes the intermodel RH feedback uncertainty*

118 The importance of uncertainty in RH feedback is highlighted in this work. However, what causes
119 the intermodel uncertainty remains unknown. Here, some potential causes are proposed. First, the
120 asymmetric contribution pattern of long-term RH feedback over tropics could be attributed to the
121 difference in Intertropical Convergence Zone (ITCZ) shift to anthropogenic forcing (Byrne et al.,
122 2018), which is closely tied to the meridional warming asymmetry we emphasize in this work.
123 Related, the asymmetric contribution pattern could also result from inherited double-ITCZ bias,
124 since the negative contribution occurs over southeastern Pacific and South Atlantic, where a
125 fictitious ITCZ is simulated by a vast majority of climate models (Tian & Dong 2020). In this case,
126 models with less double-ITCZ bias would be less affected by the drying influence of narrowed
127 ITCZ in a warming climate and thereby a larger RH feedback, vice versa. Second, given the close
128 relation between convective aggregation strength and the double-peak structure of tropical rainbelt
129 (Popp and Bony, 2019), as well as the high negative correlation between convective aggregation
130 and RH feedback (Bony et al., 2020) in observations, it is reasonable to suspect a physical causality
131 between convective aggregation strength and RH feedback. Models with stronger convective
132 aggregation would have larger double-ITCZ biases and therefore have smaller RH feedbacks.
133 Third, the tropical RH feedback uncertainty could also be related to the diversity of convective
134 schemes adopted by CMIP6 models. For example, differences in the convective adjustment to
135 exceeded saturation and the autoconversion from cloud water to rain in convective systems can
136 greatly influence relative humidity distributions (e.g., Zhao, 2014; Zhao et al., 2016).

137

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164 of cumulus precipitation microphysics. *Journal of Climate*, 29:543–560.
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166

167 **Table S1.** A list of the CMIP6 climate models analyzed in this study.

	Institution	Model	DOI piControl	DOI abrupt-4xCO2
1	CSIRO-ARCCSS	ACCESS-CM2	doi:10.22033/ESGF/CMIP6.4311	doi:10.22033/ESGF/CMIP6.4237
2	CSIRO	ACCESS-ESM1-5	doi:10.22033/ESGF/CMIP6.4312	doi:10.22033/ESGF/CMIP6.4238
3	AWI	AWI-CM-1-1-MR	doi:10.22033/ESGF/CMIP6.2777	doi:10.22033/ESGF/CMIP6.2568
4	BCC	BCC-CSM2-MR	doi:10.22033/ESGF/CMIP6.3016	doi:10.22033/ESGF/CMIP6.2845
5	BCC	BCC-ESM1	doi:10.22033/ESGF/CMIP6.3017	doi:10.22033/ESGF/CMIP6.2846
6	CAMS	CAMS-CSM1-0	doi:10.22033/ESGF/CMIP6.9797	doi:10.22033/ESGF/CMIP6.9708
7	CCCma	CanESM5	doi:10.22033/ESGF/CMIP6.3673	doi:10.22033/ESGF/CMIP6.3532
8	CAS	CAS-ESM2-0	doi:10.22033/ESGF/CMIP6.3445	doi:10.22033/ESGF/CMIP6.3174
9	NCAR	CESM2	doi:10.22033/ESGF/CMIP6.7733	doi:10.22033/ESGF/CMIP6.7519
10	NCAR	CESM2-FV2	doi:10.22033/ESGF/CMIP6.11301	doi:10.22033/ESGF/CMIP6.11285
11	NCAR	CESM2-WACCM	doi:10.22033/ESGF/CMIP6.10094	doi:10.22033/ESGF/CMIP6.10039
12	NCAR	CESM2-WACCM-FV2	doi:10.22033/ESGF/CMIP6.11302	doi:10.22033/ESGF/CMIP6.11286
13	THU	CIESM	doi:10.22033/ESGF/CMIP6.8849	doi:10.22033/ESGF/CMIP6.8807
14	CMCC	CMCC-CM2-SR5	doi:10.22033/ESGF/CMIP6.3874	doi:10.22033/ESGF/CMIP6.3731
15	CMCC	CMCC-ESM2	doi:10.22033/ESGF/CMIP6.13241	doi:10.22033/ESGF/CMIP6.13174
16	DOE	E3SM-1-0	doi:10.22033/ESGF/CMIP6.4499	doi:10.22033/ESGF/CMIP6.4491
17	EC-Earth-Consortium	EC-Earth3-AerChem	doi:10.22033/ESGF/CMIP6.4843	doi:10.22033/ESGF/CMIP6.4519
18	EC-Earth-Consortium	EC-Earth3-CC	doi:10.22033/ESGF/CMIP6.4844	doi:10.22033/ESGF/CMIP6.4520
19	EC-Earth-Consortium	EC-Earth3-Veg	doi:10.22033/ESGF/CMIP6.4848	doi:10.22033/ESGF/CMIP6.4524
20	CAS	FGOALS-f3-L	doi:10.22033/ESGF/CMIP6.3447	doi:10.22033/ESGF/CMIP6.3176
21	CAS	FGOALS-g3	doi:10.22033/ESGF/CMIP6.3448	doi:10.22033/ESGF/CMIP6.3177
22	NOAA-GFDL	GFDL-CM4	doi:10.22033/ESGF/CMIP6.8666	doi:10.22033/ESGF/CMIP6.8486
23	NOAA-GFDL	GFDL-ESM4	doi:10.22033/ESGF/CMIP6.8669	doi:10.22033/ESGF/CMIP6.8489
24	NASA-GISS	GISS-E2-1-G	doi:10.22033/ESGF/CMIP6.7380	doi:10.22033/ESGF/CMIP6.6976
25	NASA-GISS	GISS-E2-1-H	doi:10.22033/ESGF/CMIP6.7381	doi:10.22033/ESGF/CMIP6.6977
26	NASA-GISS	GISS-E2-2-G	doi:10.22033/ESGF/CMIP6.7382	doi:10.22033/ESGF/CMIP6.6978
27	CCCR-IITM	IITM-ESM	doi:10.22033/ESGF/CMIP6.3710	doi:10.22033/ESGF/CMIP6.3516
28	INM	INM-CM4-8	doi:10.22033/ESGF/CMIP6.5080	doi:10.22033/ESGF/CMIP6.4931
29	INM	INM-CM5-0	doi:10.22033/ESGF/CMIP6.5081	doi:10.22033/ESGF/CMIP6.4932
30	IPSL	IPSL-CM5A2-INCA	doi:10.22033/ESGF/CMIP6.13683	doi:10.22033/ESGF/CMIP6.13644
31	IPSL	IPSL-CM6A-LR	doi:10.22033/ESGF/CMIP6.5251	doi:10.22033/ESGF/CMIP6.5109
32	NIMS-KMA	KACE-1-0-G	doi:10.22033/ESGF/CMIP6.8425	doi:10.22033/ESGF/CMIP6.8348
33	MIROC	MIROC6	doi:10.22033/ESGF/CMIP6.5711	doi:10.22033/ESGF/CMIP6.5411
34	HAMMOZ-Consortium	MPI-ESM-1-2-HAM	doi:10.22033/ESGF/CMIP6.5037	doi:10.22033/ESGF/CMIP6.5000
35	MPI-M	MPI-ESM1-2-HR	doi:10.22033/ESGF/CMIP6.6674	doi:10.22033/ESGF/CMIP6.6458
36	MPI-M	MPI-ESM1-2-LR	doi:10.22033/ESGF/CMIP6.6675	doi:10.22033/ESGF/CMIP6.6459
37	MRI	MRI-ESM2-0	doi:10.22033/ESGF/CMIP6.6900	doi:10.22033/ESGF/CMIP6.6755
38	NUIST	NESM3	doi:10.22033/ESGF/CMIP6.8776	doi:10.22033/ESGF/CMIP6.8719
39	NCC	NorESM2-LM	doi:10.22033/ESGF/CMIP6.8217	doi:10.22033/ESGF/CMIP6.7836
40	NCC	NorESM2-MM	doi:10.22033/ESGF/CMIP6.8221	doi:10.22033/ESGF/CMIP6.7840
41	SNU	SAM0-UNICON	doi:10.22033/ESGF/CMIP6.7791	doi:10.22033/ESGF/CMIP6.7783
42	AS-RCEC	TaiESM1	doi:10.22033/ESGF/CMIP6.9798	doi:10.22033/ESGF/CMIP6.9709

169 **Table S2.** A list of the CMIP6 climate models analyzed in Figure S1.

	Institution	Model	DOI historical	DOI SSP2-4.5
1	CSIRO-ARCCSS	ACCESS-CM2	doi:10.22033/ESGF/CMIP6.4271	doi:10.22033/ESGF/CMIP6.4321
2	CSIRO	ACCESS-ESM1-5	doi:10.22033/ESGF/CMIP6.4272	doi:10.22033/ESGF/CMIP6.4322
3	AWI	AWI-CM-1-1-MR	doi:10.22033/ESGF/CMIP6.2686	doi:10.22033/ESGF/CMIP6.2800
4	BCC	BCC-CSM2-MR	doi:10.22033/ESGF/CMIP6.2948	doi:10.22033/ESGF/CMIP6.3030
5	CAMS	CAMS-CSM1-0	doi:10.22033/ESGF/CMIP6.9754	doi:10.22033/ESGF/CMIP6.11047
6	CCCma	CanESM5	doi:10.22033/ESGF/CMIP6.3610	doi:10.22033/ESGF/CMIP6.3685
7	CAS	CAS-ESM2-0	doi:10.22033/ESGF/CMIP6.3353	***
8	NCAR	CESM2	doi:10.22033/ESGF/CMIP6.7627	doi:10.22033/ESGF/CMIP6.7748
9	NCAR	CESM2-WACCM	doi:10.22033/ESGF/CMIP6.10071	doi:10.22033/ESGF/CMIP6.10101
10	THU	CIESM	doi:10.22033/ESGF/CMIP6.8843	doi:10.22033/ESGF/CMIP6.8858
11	CMCC	CMCC-CM2-SR5	doi:10.22033/ESGF/CMIP6.3825	doi:10.22033/ESGF/CMIP6.3889
12	CMCC	CMCC-ESM2	doi:10.22033/ESGF/CMIP6.13195	doi:10.22033/ESGF/CMIP6.13252
13	EC-Earth-Consortium	EC-Earth3-CC	doi:10.22033/ESGF/CMIP6.4702	doi:10.22033/ESGF/CMIP6.15631
14	EC-Earth-Consortium	EC-Earth3-Veg	doi:10.22033/ESGF/CMIP6.4706	doi:10.22033/ESGF/CMIP6.4882
15	CAS	FGOALS-f3-L	doi:10.22033/ESGF/CMIP6.3355	doi:10.22033/ESGF/CMIP6.3468
16	CAS	FGOALS-g3	doi:10.22033/ESGF/CMIP6.3356	doi:10.22033/ESGF/CMIP6.3469
17	NOAA-GFDL	GFDL-CM4	doi:10.22033/ESGF/CMIP6.8594	doi:10.22033/ESGF/CMIP6.9263
18	NOAA-GFDL	GFDL-ESM4	doi:10.22033/ESGF/CMIP6.8597	doi:10.22033/ESGF/CMIP6.8686
19	CCCR-IITM	IITM-ESM	doi:10.22033/ESGF/CMIP6.3708	doi:10.22033/ESGF/CMIP6.14748
20	INM	INM-CM4-8	doi:10.22033/ESGF/CMIP6.5069	doi:10.22033/ESGF/CMIP6.12327
21	INM	INM-CM5-0	doi:10.22033/ESGF/CMIP6.5070	doi:10.22033/ESGF/CMIP6.12328
22	IPSL	IPSL-CM6A-LR	doi:10.22033/ESGF/CMIP6.5195	doi:10.22033/ESGF/CMIP6.5264
23	NIMS-KMA	KACE-1-0-G	doi:10.22033/ESGF/CMIP6.8378	doi:10.22033/ESGF/CMIP6.8435
24	MIROC	MIROC6	doi:10.22033/ESGF/CMIP6.5603	doi:10.22033/ESGF/CMIP6.5746
25	MPI-M	MPI-ESM1-2-HR	doi:10.22033/ESGF/CMIP6.6594	###
	DKRZ		###	doi:10.22033/ESGF/CMIP6.4398
26	MPI-M	MPI-ESM1-2-LR	doi:10.22033/ESGF/CMIP6.6595	doi:10.22033/ESGF/CMIP6.6693
27	MRI	MRI-ESM2-0	doi:10.22033/ESGF/CMIP6.6842	doi:10.22033/ESGF/CMIP6.6910
28	NUIST	NESM3	doi:10.22033/ESGF/CMIP6.8769	doi:10.22033/ESGF/CMIP6.8781
29	NCC	NorESM2-LM	doi:10.22033/ESGF/CMIP6.8036	doi:10.22033/ESGF/CMIP6.8253
30	NCC	NorESM2-MM	doi:10.22033/ESGF/CMIP6.8040	doi:10.22033/ESGF/CMIP6.8255
31	AS-RCEC	TaiESM1	doi:10.22033/ESGF/CMIP6.9755	doi:10.22033/ESGF/CMIP6.9808

***: DOI number is not available;

###: Simulation is not available.

171 **Table S3.** Global-mean values of cloud, clear-sky LR+WV and RH feedback for CMIP6 models
172 on both interannual (piControl) and long-term timescales.

	Model	Interannual feedback			Long-term feedback		
		Cloud	LR+WV	RH	Cloud	LR+WV	RH
1	ACCESS-CM2	0.481	1.156	-0.404	0.873	1.413	-0.2
2	ACCESS-ESM1-5	0.958	1.375	-0.16	0.669	1.506	-0.08
3	AWI-CM-1-1-MR	0.188	1.492	-0.045	0.3	1.552	-0.071
4	BCC-CSM2-MR	0.805	1.163	-0.179	0.619	1.427	-0.139
5	BCC-ESM1	0.513	1.106	-0.174	0.686	1.411	-0.133
6	CAMS-CSM1-0	-0.218	1.441	-0.18	-0.144	1.616	-0.02
7	CanESM5	0.728	1.346	-0.078	0.883	1.572	-0.022
8	CAS-ESM2-0	0.096	1.519	-0.186	0.566	1.566	-0.073
9	CESM2	1.277	1.308	-0.223	1.152	1.49	-0.13
10	CESM2-FV2	0.859	1.104	-0.403	1.202	1.409	-0.16
11	CESM2-WACCM	1.624	1.266	-0.23	1.417	1.472	-0.14
12	CESM2-WACCM-FV2	0.882	1.135	-0.386	1.28	1.376	-0.198
13	CIESM	0.629	1.184	-0.282	0.881	1.463	-0.183
14	CMCC-CM2-SR5	0.519	1.489	-0.062	0.662	1.541	-0.094
15	CMCC-ESM2	0.203	1.372	-0.214	0.648	1.539	-0.087
16	E3SM-1-0	0.546	1.213	-0.173	1.079	1.5	-0.085
17	EC-Earth3-AerChem	0.151	1.535	0.071	0.338	1.65	0.035
18	EC-Earth3-CC	0.422	1.518	0.055	0.473	1.662	0.039
19	EC-Earth3-Veg	0.439	1.498	0.014	0.476	1.667	0.042
20	FGOALS-f3-L	-0.284	1.068	-0.434	0.127	1.435	-0.132
21	FGOALS-g3	0.032	1.359	-0.039	0.164	1.649	0.077
22	GFDL-CM4	0.587	1.283	-0.17	0.738	1.51	-0.05
23	GFDL-ESM4	0.928	1.325	-0.181	0.765	1.478	-0.096
24	GISS-E2-1-G	-0.156	1.474	-0.107	0.151	1.508	-0.086
25	GISS-E2-1-H	-0.073	1.231	-0.198	0.184	1.572	-0.021
26	GISS-E2-2-G	-0.073	1.272	-0.102	0.085	1.563	-0.057
27	IITM-ESM	-0.192	1.799	0.358	0.014	1.556	0.007
28	INM-CM4-8	0.105	1.556	0.164	-0.064	1.6	0.037
29	INM-CM5-0	0.215	1.478	0.089	-0.084	1.554	-0.011
30	IPSL-CM5A2-INCA	0.951	1.697	0.193	1.125	1.591	-0.022
31	IPSL-CM6A-LR	0.544	1.563	0.086	0.523	1.615	0.013
32	KACE-1-0-G	0.811	1.331	-0.162	0.916	1.404	-0.207
33	MIROC6	0.525	1.477	-0.118	0.199	1.497	-0.113
34	MPI-ESM-1-2-HAM	0.148	1.67	0.099	-0.21	1.578	-0.011
35	MPI-ESM1-2-HR	0.126	1.418	-0.032	0.299	1.552	-0.068
36	MPI-ESM1-2-LR	0.274	1.569	0.011	0.198	1.535	-0.067
37	MRI-ESM2-0	0.735	1.234	-0.15	0.553	1.379	-0.181
38	NESM3	0.309	1.518	0.023	0.471	1.549	-0.041
39	NorESM2-LM	0.803	1.542	-0.07	0.66	1.553	-0.102
40	NorESM2-MM	0.824	1.534	-0.091	0.633	1.56	-0.104
41	SAM0-UNICON	0.552	1.317	-0.113	0.832	1.323	-0.277
42	TaiESM1	0.425	1.312	-0.199	0.795	1.464	-0.141

174 **Table S4.** Global-mean values of all-sky LR+WV, RH and $\tilde{R}$ feedback for CMIP6 models on both
175 interannual (piControl) and long-term timescales.

	Model	Interannual feedback			Long-term feedback		
		LR+WV	RH	LR	LR+WV	RH	LR
1	ACCESS-CM2	1.077	-0.169	0.102	0.986	-0.13	-0.111
2	ACCESS-ESM1-5	1.274	-0.028	0.176	1.118	-0.034	-0.044
3	AWI-CM-1-1-MR	1.224	0.016	0.05	1.11	-0.046	-0.077
4	BCC-CSM2-MR	1.16	-0.099	0.374	1.01	-0.101	-0.09
5	BCC-ESM1	1.141	-0.124	0.43	1.001	-0.095	-0.086
6	CAMS-CSM1-0	1.074	-0.01	-0.187	1.102	-0.01	-0.15
7	CanESM5	1.094	-0.016	0.035	1.057	0.005	-0.19
8	CAS-ESM2-0	1.199	-0.024	-0.065	1.188	-0.047	0.022
9	CESM2	1.11	-0.029	-0.04	1.029	-0.067	-0.162
10	CESM2-FV2	1.024	-0.087	-0.065	0.996	-0.09	-0.134
11	CESM2-WACCM	1.112	-0.069	0.059	1.032	-0.069	-0.151
12	CESM2-WACCM-FV2	1.043	-0.073	-0.064	0.956	-0.124	-0.151
13	CIESM	1.028	-0.116	0.066	1.07	-0.128	-0.031
14	CMCC-CM2-SR5	1.194	-0.021	0.073	1.075	-0.059	-0.116
15	CMCC-ESM2	1.058	-0.078	-0.077	1.07	-0.047	-0.132
16	E3SM-1-0	1.153	-0.011	0.168	1.034	-0.042	-0.167
17	EC-Earth3-AerChem	1.398	0.071	0.32	1.214	0.034	-0.022
18	EC-Earth3-CC	1.382	0.081	0.289	1.228	0.038	-0.011
19	EC-Earth3-Veg	1.363	0.059	0.264	1.243	0.045	-0.004
20	FGOALS-f3-L	0.963	-0.191	0.04	1.071	-0.089	-0.01
21	FGOALS-g3	1.191	0.089	0.065	1.203	0.074	-0.062
22	GFDL-CM4	1.2	-0.044	0.191	1.06	-0.026	-0.128
23	GFDL-ESM4	1.155	-0.085	0.134	0.972	-0.061	-0.22
24	GISS-E2-1-G	0.978	0.03	-0.331	0.889	-0.055	-0.349
25	GISS-E2-1-H	1.048	-0.051	0.057	1.09	-0.009	-0.122
26	GISS-E2-2-G	1.179	0.004	0.237	0.983	-0.028	-0.294
27	IITM-ESM	1.557	0.43	0.037	1.005	0.02	-0.255
28	INM-CM4-8	1.582	0.163	0.515	1.22	0.037	0.01
29	INM-CM5-0	1.458	0.099	0.44	1.193	0.001	0.014
30	IPSL-CM5A2-INCA	1.301	0.189	-0.023	0.999	-0.023	-0.256
31	IPSL-CM6A-LR	1.308	0.093	0.153	1.118	0.021	-0.13
32	KACE-1-0-G	1.199	-0.061	0.203	0.987	-0.13	-0.116
33	MIROC6	1.036	0.003	-0.252	0.98	-0.058	-0.246
34	MPI-ESM-1-2-HAM	1.381	0.103	0.124	1.066	-0.015	-0.145
35	MPI-ESM1-2-HR	1.21	0.044	0.116	1.09	-0.035	-0.117
36	MPI-ESM1-2-LR	1.248	0.084	-0.039	1.003	-0.045	-0.217
37	MRI-ESM2-0	1.254	-0.007	0.32	0.978	-0.119	-0.102
38	NESM3	1.268	0.038	0.138	1.042	-0.032	-0.139
39	NorESM2-LM	1.272	0.096	-0.069	1.054	-0.013	-0.254
40	NorESM2-MM	1.199	0.058	-0.145	1.022	-0.021	-0.304
41	SAM0-UNICON	1.257	-0.034	0.319	0.901	-0.175	-0.179
42	TaiESM1	1.183	-0.014	0.093	1.043	-0.08	-0.099

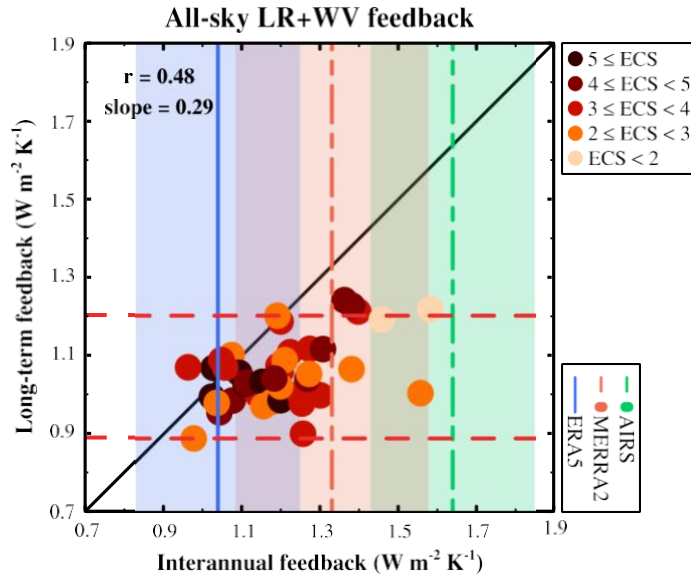


Figure S1. Same as Figure 1b, except for all-sky conditions.

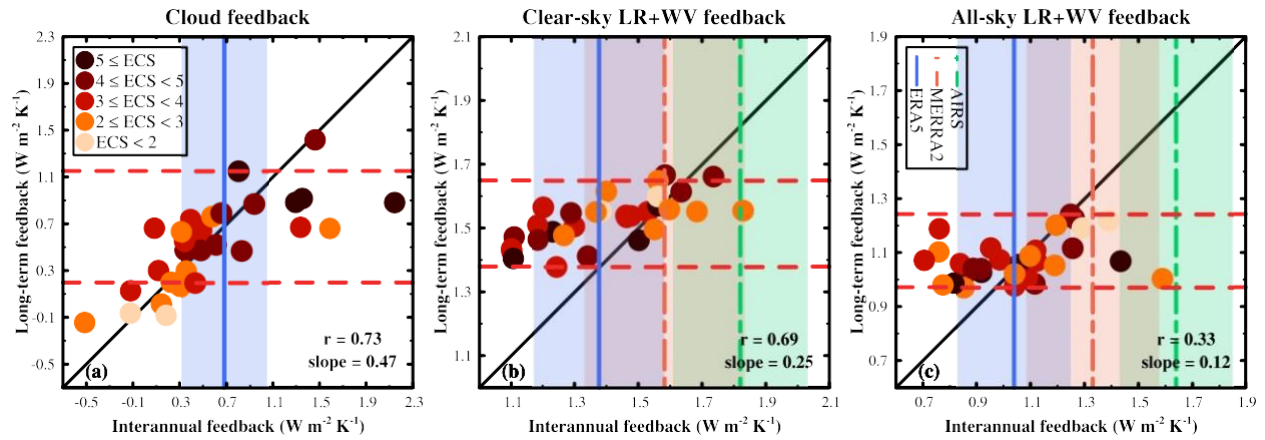


Figure S2. (a-c) are same as Figure 1a, 1b and Figure S1, except that the interannual feedbacks here are calculated using historical period 2001-2019 (including period 2015-2019 from SSP2-4.5), which matches CERES observations, from models listed in Table S2.

Figure S3. Cross-model regressions of local (a-b) cloud, (c-d) low cloud and (e-f) high cloud feedbacks against global-mean cloud feedback for both (left) interannual and (right) long-term timescales. Hatching indicates area where regression is statistically significant at the 95% level.

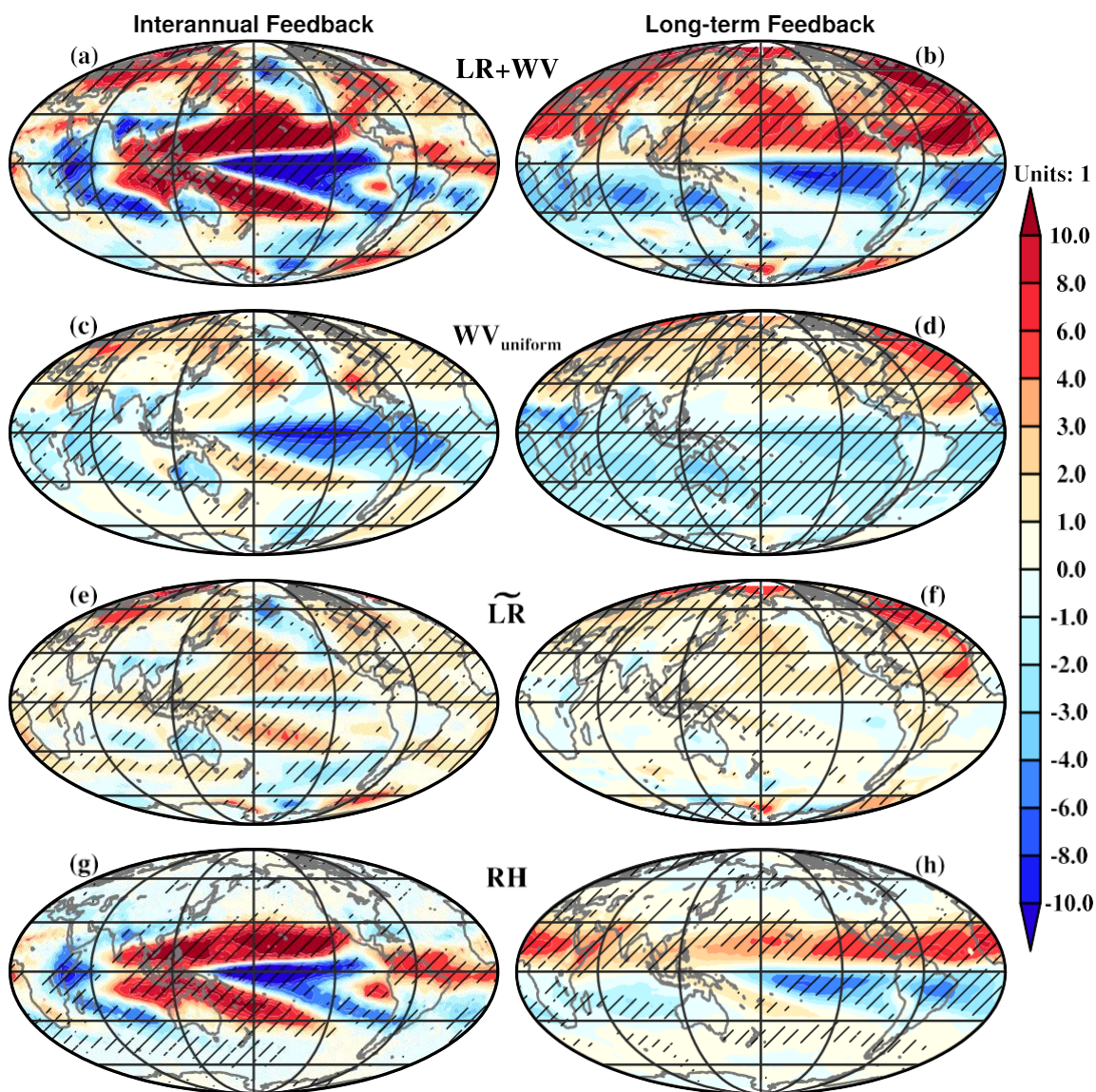


Figure S4. Same as Figure 3a-h, except for all-sky conditions.

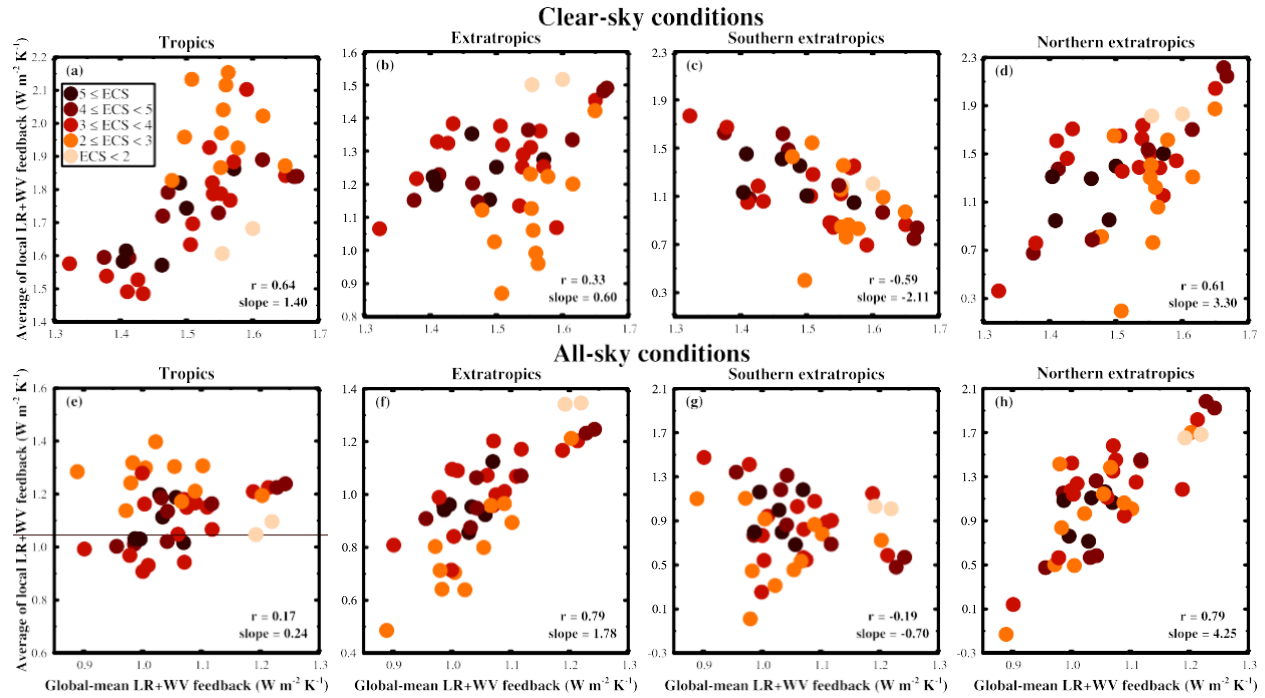


Figure S5. Comparison between long-term global-mean and regional average of local LR+WV feedback over (a & e) tropics, (b & f) extratropics, (c & g) southern extratropics and (d & h) northern extratropics under both (top) clear-sky and (bottom) all-sky conditions.

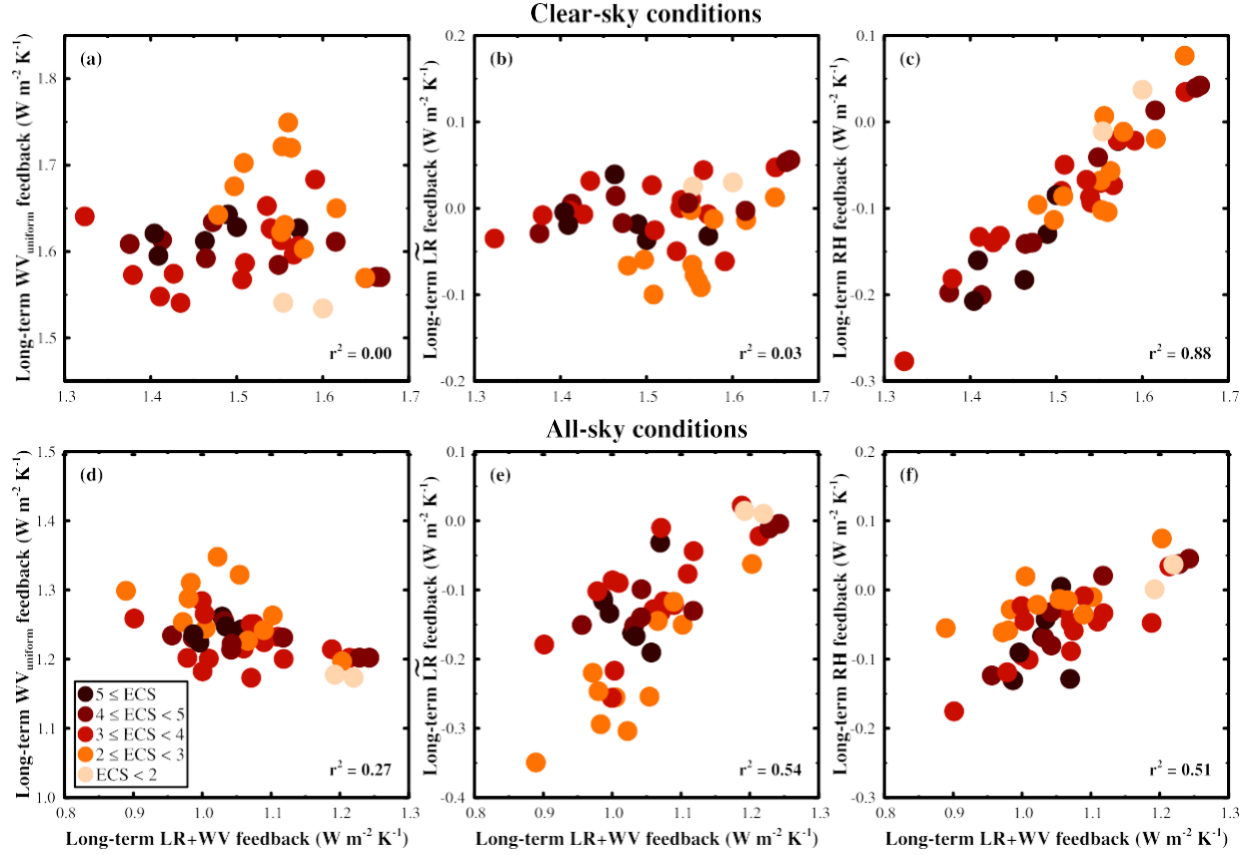


Figure S6. Comparison between long-term LR+WV feedback and its components [i.e., (a & d) $WV_{uniform}$, (b & e) R and (c & f) RH feedbacks] under both (top) clear-sky and (bottom) all-sky conditions.

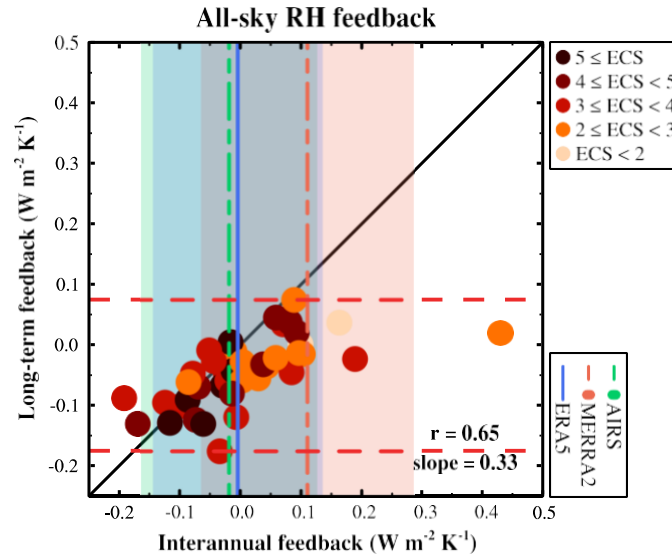


Figure S7. Same as Figure 3j, except for all-sky conditions.

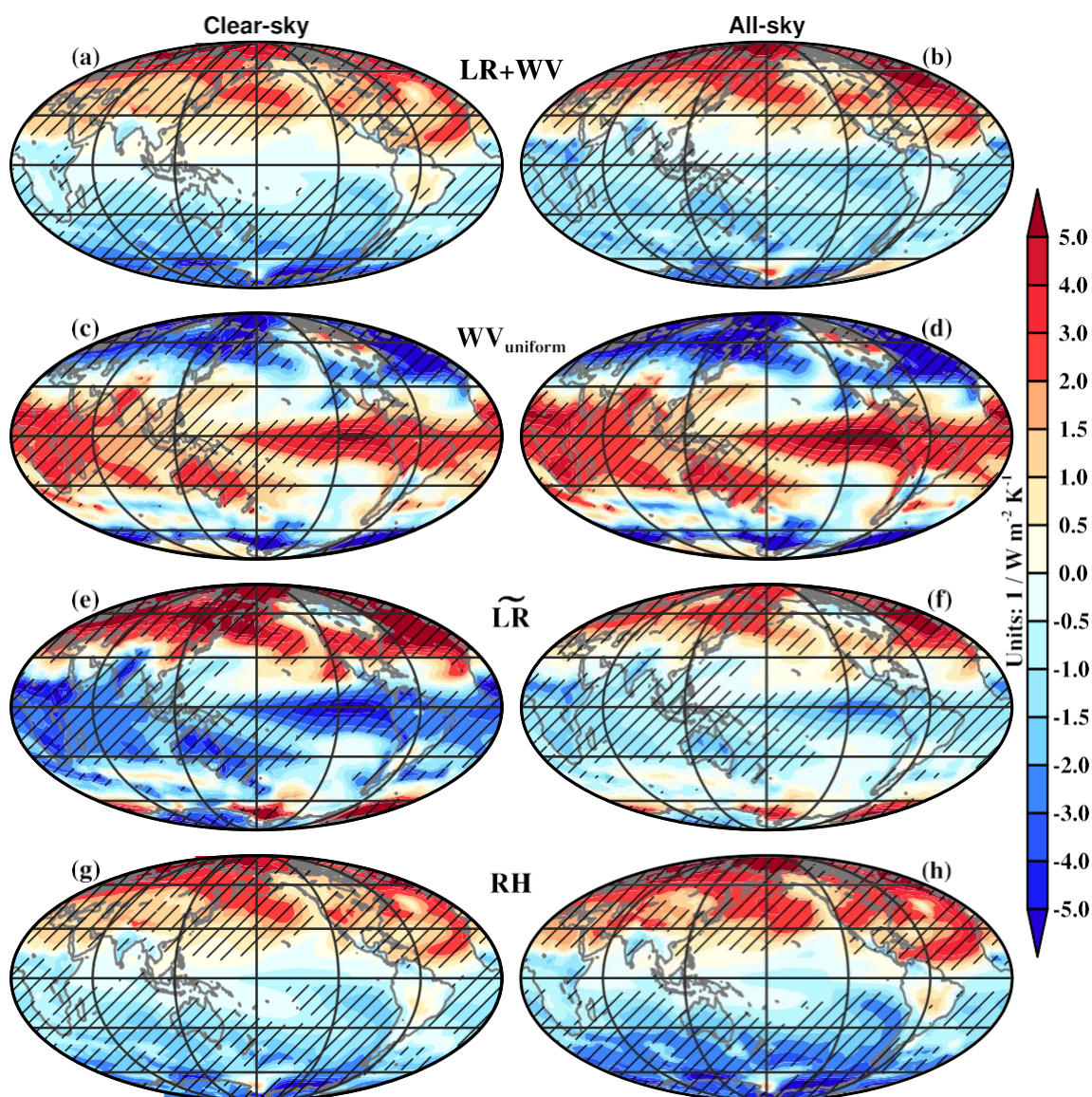


Figure S8. Cross-model regressions of local surface temperature sensitivity to global-mean long-term (a-b) LR+WV, (c-d) $WV_{uniform}$, (e-f) $\tilde{R}$ and (g-h) RH feedbacks on both (left) clear-sky and (right) all-sky conditions. Hatching indicates area where regression is statistically significant at the 95% level.

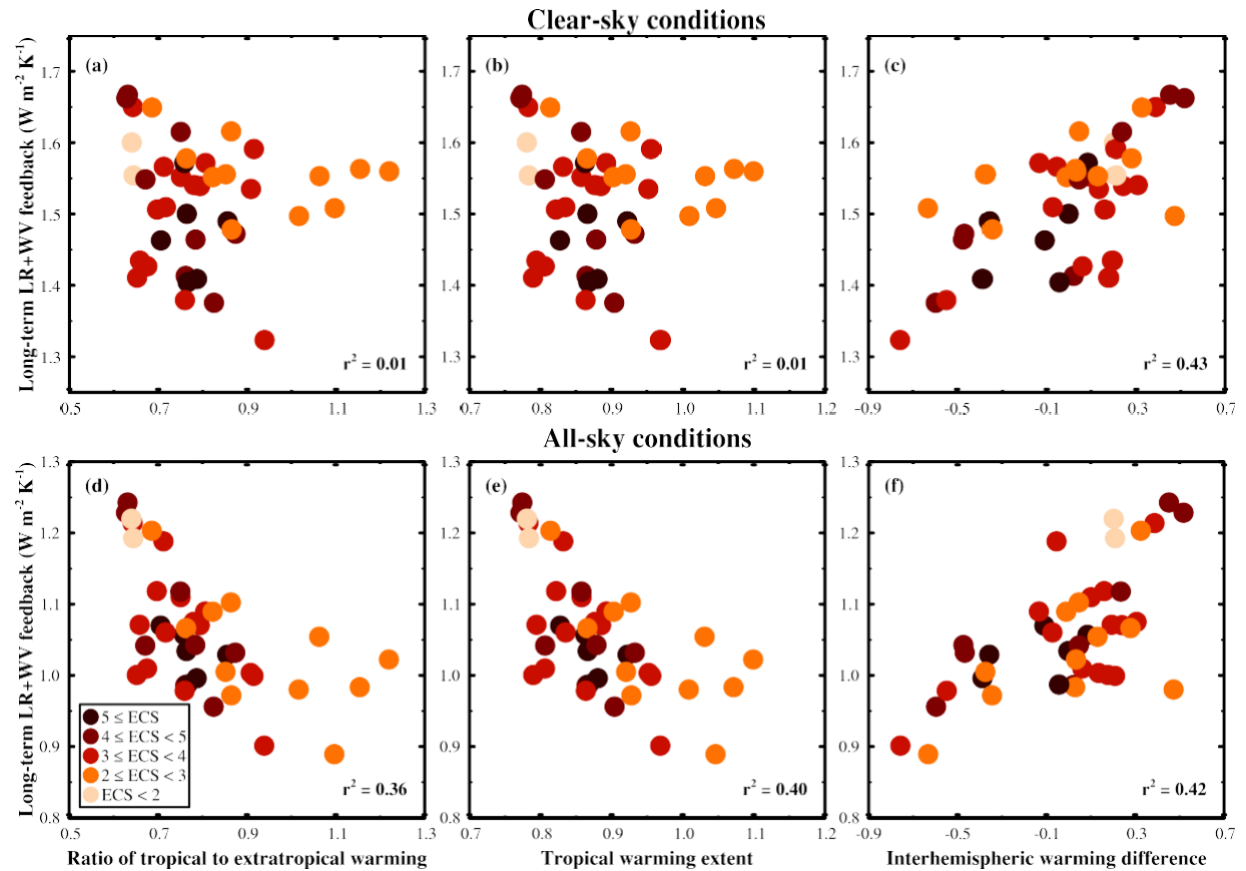


Figure S9. Scatterplots of (a & d) the ratio of tropical to extratropical surface warming, (b & e) tropical warming extent and (c & f) interhemispheric warming difference versus global-mean long-term LR+WV feedback under both (top) clear-sky and (bottom) all-sky conditions.

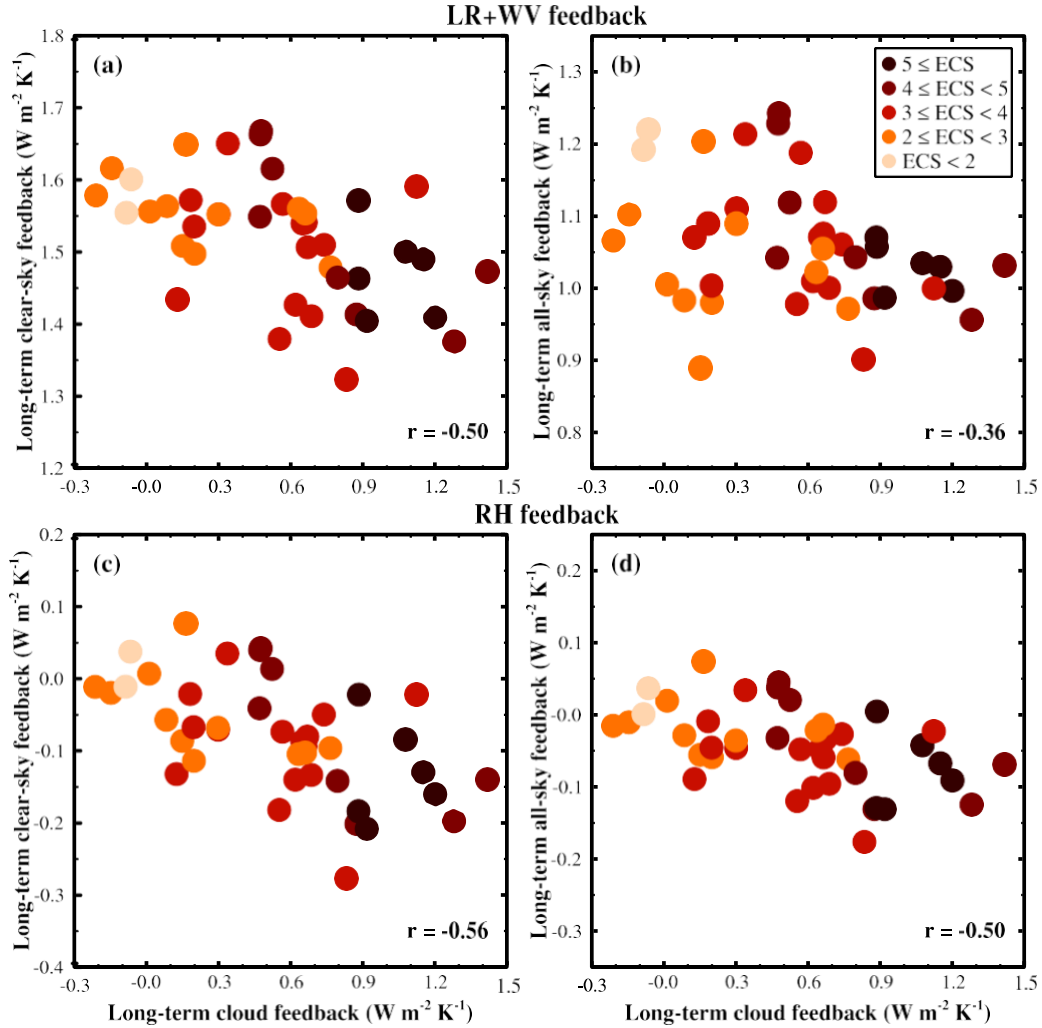


Figure S10. Comparison between long-term cloud feedback and both (a-b) LR+WV and (c-d) RH feedbacks under both (left) clear-sky and (right) all-sky conditions in 42 CMIP6 models. The correlations are statistically significant at the 99% level, except that the correlation between long-term cloud feedback and all-sky LR+WV feedbacks is statistically significant at the 95% level.

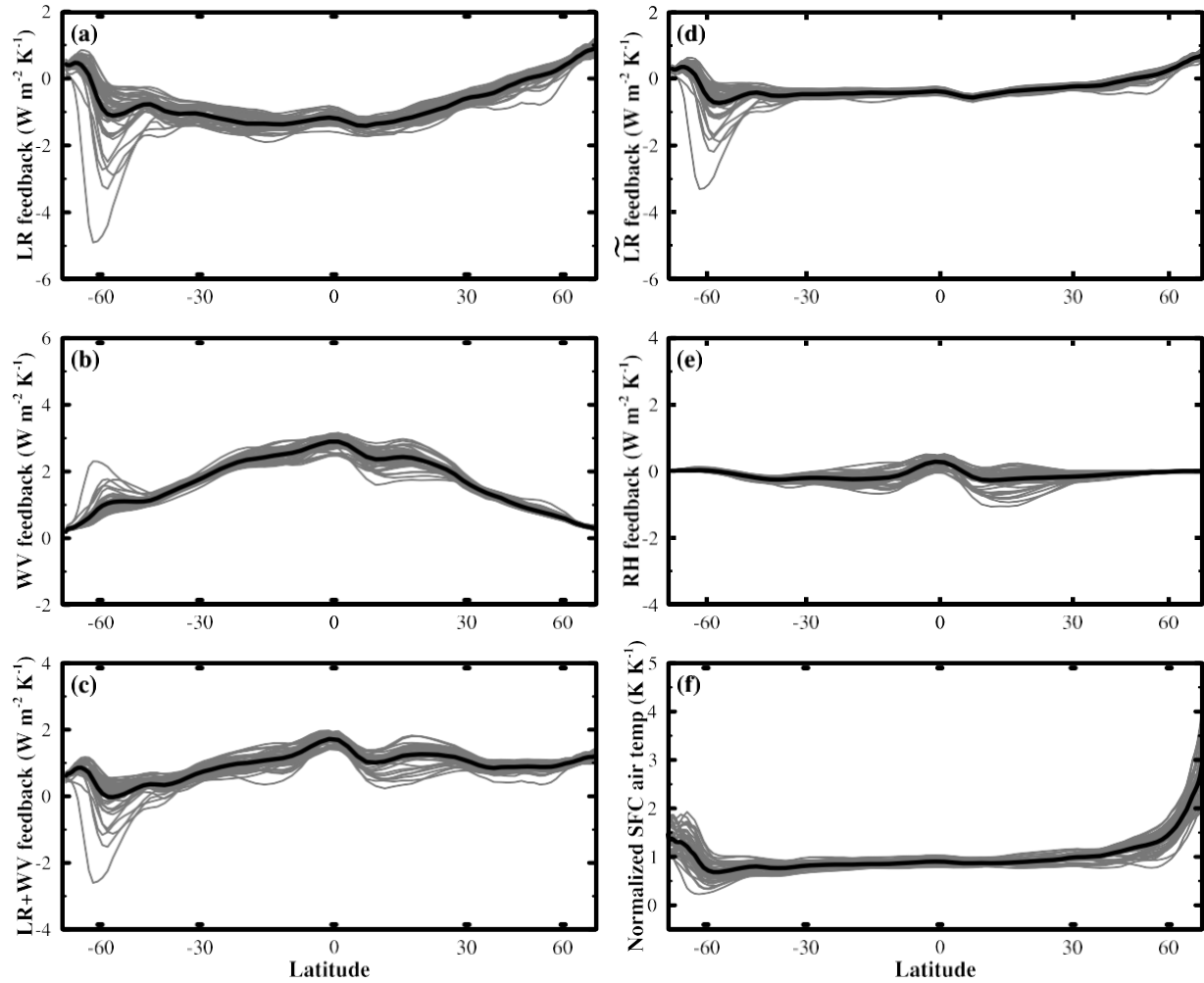


Figure S11. The zonal feedbacks (zonal mean radiative responses divided by zonal mean surface temperature anomaly) for (a) LR, (b) WV, (c) LR + WV, (d) $\tilde{R}$ and (e) RH. Results are for all 42 models (gray lines). (f) The zonal mean surface warming normalized by the model's global average surface warming. The multi-model mean is indicated by a solid black line. Note that the x axis is scaled by the sine of latitude, the x-axis limits are $\pm 90^\circ$, and the y-axis ranges are the same in (a)–(e).

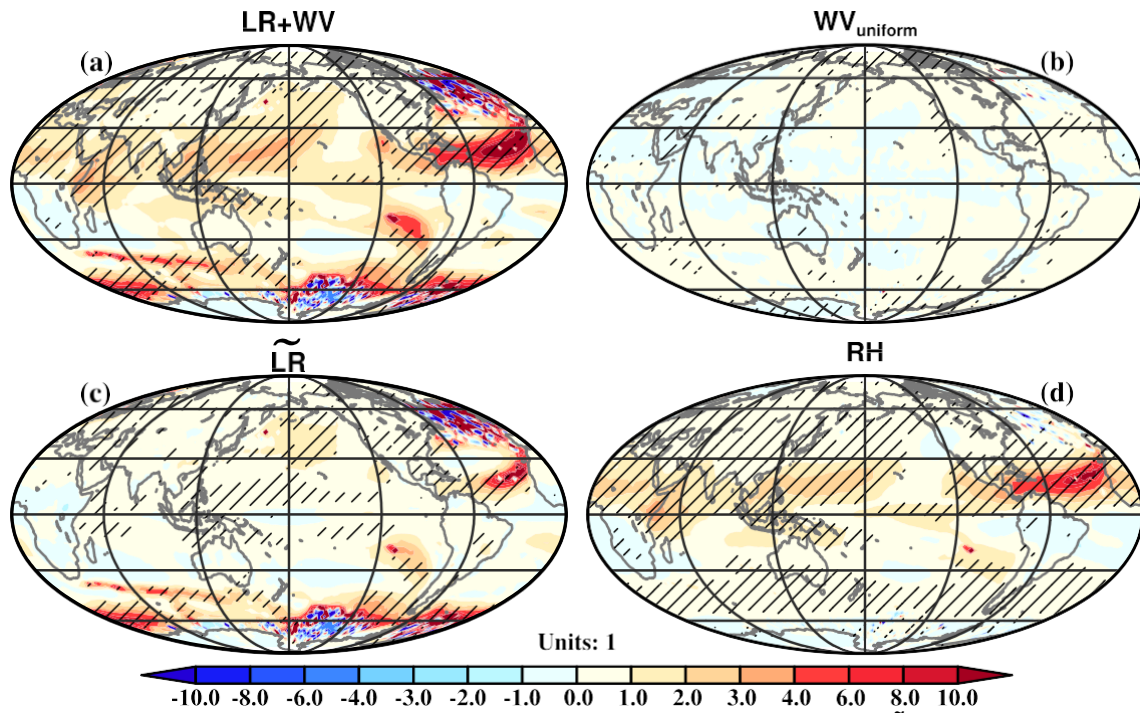


Figure S12. (a-d) are same as Figure S3b (LR+WV), S3d (WV_{uniform}), S3f ($\tilde{LR}$) and S3h (RH), except that the feedback is calculated in the way Po-Chedley et al. (2018) did.

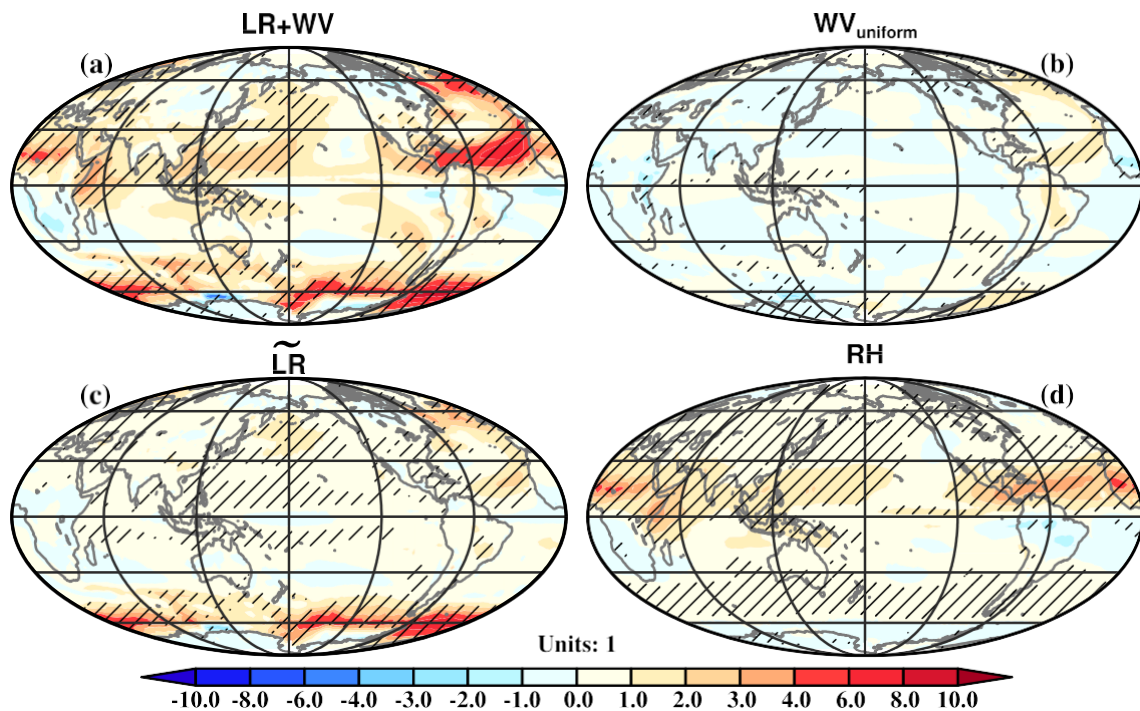


Figure S13. Same as Figure S13, except that the local feedback is calculated using zonal-mean surface temperature anomaly.