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Insights from a Refined Decomposition of Cloud Feedbacks

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Key Points.

- Three robust cloud feedbacks in GCMs: low amount, low optical depth, and non-low altitude.
- Positive feedback from rising high clouds is smaller and better constrained than commonly quoted.
- Low cloud amount feedback is single largest contributor to spread in net cloud feedback.

Abstract

Decomposing cloud feedback into components due to changes in several gross cloud properties provides valuable insights into its physical causes. Here we present a refined decomposition that separately considers changes in free tropospheric and low cloud properties, better connecting feedbacks to individual governing processes and avoiding ambiguities present in a commonly-used decomposition. It reveals that three net cloud feedback components are robustly nonzero: positive feedbacks from increasing free tropospheric cloud altitude and decreasing low cloud cover and a negative feedback from increasing low cloud optical depth. Low cloud amount feedback is the dominant contributor to spread in net cloud feedback, but its anti-correlation with other components damps overall spread. The ensemble mean free tropospheric cloud altitude feedback is roughly 60% as large as the standard cloud altitude feedback because it avoids aliasing in low cloud reductions. Implications for the "null hypothesis" climate sensitivity from well-understood and robustly-simulated feedbacks are discussed.

1. Introduction

In response to a positive radiative forcing, the climate system warms, which induces feedbacks that modify the amount of warming necessary to re-equilibrate. The stronger the positive feedbacks operating in the climate system, the larger the resultant warming for a given positive radiative forcing. Most of the diversity in climate model projections of how much equilibrium warming occurs for a doubling of atmospheric carbon dioxide is driven by inter-model spread in the cloud feedback [*Dufresne and Bony*, 2008; *Caldwell et al.*, 2016]. Thus, an abiding goal of climate science is to reduce uncertainty in cloud feedback. The global mean cloud feedback is the sum of many individual cloud feedbacks that vary in both strength and sign as a function of latitude, longitude, altitude, optical depth, season, and band (longwave versus shortwave). Important steps in narrowing uncertainty in the cloud feedback are to accurately quantify it in global climate models (GCMs) and to understand the contributions to it from specific processes that change clouds.

Recently cloud radiative kernels have been developed to quantify the contribution to the cloud feedback from changes in 49 individual cloud types [*Zelinka et al.*, 2012a]. These cloud types are classified by cloud top pressure (CTP) and visible optical depth (τ) based on the International Satellite Cloud Climatology Project (ISCCP [*Rossow and Schiffer*, 1999]). It is customary to aggregate these changes into a smaller number of cloud types by summing the responses within specific altitude or optical depth ranges [*Zelinka et al.*, 2012a] or to decompose the feedback into contributions from changes in cloud amount, altitude, and optical depth [*Zelinka et al.*, 2012b, 2013]. This has led to useful insights regarding the cloud feedbacks that are robustly simulated across models and those exhibiting substantial inter-model spread [*Zelinka et al.*, 2012b, 2013; *Boucher et al.*, 2013].

While these techniques are appealing and informative, they can be somewhat subjective and risk combining disparate responses that are better considered in isolation. Here we highlight some important ambiguities in the cloud feedback decomposition of *Zelinka et al.* [2012b, 2013] that can result in misleading implications about the magnitude, robustness, and/or uncertainty in certain cloud feedbacks. We then present a refined decomposition that strives to strike a more optimal balance between (1) aggregating the 49 individual cloud responses into a smaller number of coherent responses that can be easily understood and (2) maintaining a sufficient level of detail in which a given cloud property change is tied unambiguously to a single specific physical processes.

2. Data and Methods

We use cloud radiative kernels [*Zelinka et al.*, 2012a] along with output from the ISCCP simulator [*Klein and Jakob*, 1999; *Webb et al.*, 2001] to calculate cloud feedbacks. Cloud radiative kernels quantify the impact on TOA radiative fluxes of changes in the fractional coverage of clouds segregated CTP and τ. Multiplying the monthly- and spatially-resolved kernels by the change in CTP- and τ-resolved cloud fraction provided by the ISCCP simulator yields an estimate of the TOA radiation anomaly induced by each cloud type. Summing over the entire histogram and normalizing by the change in global mean surface air temperature (ΔT_s), yields the cloud feedback.

Cloud feedbacks for the CFMIP1 models are derived using CO_2 doubling experiments in atmospheric models coupled to slab oceans as in *Zelinka et al.* [2012a], while those for the CFMIP2 models are derived using the abrupt4xCO2 experiments as in *Zelinka et al.* [2013]. Unlike the methodology applied to the CFMIP2 models, that applied to the CFMIP1 models does not allow us to separate rapid cloud adjustments to CO_2 from "true" temperature-mediated cloud feedbacks. However we do not expect this to have a large impact on our results because the slab ocean experiments of CFMIP1 were run to equilibrium, which tends to reduce the impact of early adjustments on the feedback calculation [*Zelinka et al.*, 2013].

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3. Features of the Standard Decomposition

Following *Zelinka et al.* [2012b], with modifications by *Zelinka et al.* [2013], we decompose the cloud feedback into amount, altitude, optical depth, and residual components. The amount component quantifies the feedback arising from the change in total cloud fraction holding the relative proportions of cloud fractions in each CTP and τ bin constant. The altitude feedback is the component arising from the anomalous vertical distribution of clouds holding the total amount and optical depth distribution fixed. The optical depth feedback is the component arising from anomalous optical depth distribution of clouds, holding the total amount and vertical distribution fixed.

The global mean longwave (LW), shortwave (SW), and net cloud feedbacks for the CFMIP1 and CFMIP2 models, broken down into amount, altitude, optical depth, and residual components are shown in Figure 1a. These are discussed in detail in *Zelinka et al.* [2012b, 2013], so we will only highlight the key results here. The multi-model mean net cloud feedback is positive, receiving roughly equal contributions from LW and SW components, and exhibits considerable inter-model spread. Robust but widely varying reductions in total cloudiness among models lead to a robustly positive but widely varying SW cloud amount feedback that is partially offset by a weaker LW cloud amount feedback. The net cloud amount feedback is thus robustly positive and has less inter-model spread than its SW or LW components. Overall increases in cloud top altitude lead to a strong but widely varying net cloud altitude feedback. In the multi-model mean, it is the strongest net cloud feedback. Owing to the predominance of models with increases in cloud optical depth, especially among cold clouds at high latitudes or altitudes (e.g., Fig. 1c of *Zelinka et al.* [2012b] and Fig. 8f of *Zelinka et al.* [2013]), the cloud optical depth feedback is generally negative in the SW but offset slightly in the LW due to increased optical depth and hence longwave emissivity of high clouds [*Stephens*, 1978]. Thus the net cloud optical depth feedback is negative on average, with a smaller multi-model mean magnitude than the altitude or amount feedbacks, but with similar inter-model spread. It is the only feedback that is negative in the majority of models and in the multi-model mean. Only one model in this ensemble (MIROC5) has a negative cloud feedback, which arises from having a near-zero cloud amount feedback, a small LW altitude feedback, and a stronger negative optical depth feedback than most models.

The proportionate change in cloud fraction used in the calculation of the cloud amount feedback assumes that the cloud fraction change in each CTP and τ bin has the same sign as the change in total cloud fraction and occurs in proportion to the amount that is present in the mean state. Given that high and low clouds exist in vastly different environments and changes in their coverage are governed by distinct physical processes that often act independently, the change in total cloud fraction at any given location is often the residual of opposing high and low cloud responses. Thus, the physical interpretation of the cloud amount feedback is obscured by its poor connection to a single cloud-controlling process. Moreover, because changes in clouds that differ from the proportionate change are ascribed to changes in cloud altitude and optical depth, the linkage between these feedbacks and their governing physics may also be obscured. In the Supporting Information we discuss several specific examples of this.

4. A Refined Decomposition

To provide a more physically motivated description of cloud amount, altitude and optical depth feedbacks, we use the same decomposition as *Zelinka et al.* [2013], but simply perform the decomposition separately for low clouds with CTP >680 hPa and for non-low clouds with CTP ≤680 hPa. This altitude separation is motivated by the tendency for boundary layer clouds to behave distinctly from clouds in the free troposphere, and for free tropospheric clouds to change coherently. For example, both mid-level and high clouds tend to both shift upwards with global warming. Because mid-level and high cloud feedbacks are considered together rather than distinctly in the refined decomposition, we recommend using it in concert with the standard breakdown of high, mid-level, and low cloud feedbacks [*Zelinka et al.*, 2012a].

We regard low clouds with CTP ≤680 hPa as boundary layer clouds and non-low clouds with CTP <680 hPa as free tropospheric clouds in this paper, though we acknowledge that these may not perfectly correspond. The top of the boundary layer is usually at pressures exceeding 680 hPa, but clouds in the 680< CTP ≤800 hPa bin in subtropical subsidence regions are actually boundary layer clouds for which the simulator adjusts the CTP, mimicking the difficulty ISCCP has in determining true CTP under strong capping inversions [*Garay et al.*, 2008]. In regions without strong capping inversions, it may be less appropriate to consider these as boundary layer clouds. Furthermore, the ISCCP simulator will (purposely) assign clouds to middle-levels if thin cirrus lies over low clouds [*Marchand et al.*, 2010; *Mace et al.*, 2011]. In these situations, changes in middle-level cloud may actually be caused by changes in cirrus, changes in low cloud, or a combination of both. Having noted these caveats, we proceed under the assumption that the vast majority of clouds with CTP >680hPa are boundary layer clouds and the vast majority of clouds with CTP ≤680hPa have their tops in the free troposphere.

Figure 1b and c shows global mean LW, SW, and net cloud feedbacks, decomposed separately for non-low and low clouds. Maps of the multi-model mean net total, amount, altitude, and optical depth feedbacks decomposed using the entire histogram, and using only the non-low and low portion of the histogram are shown in Figure 2. LW and SW counterparts are shown in Figures S5 and S6, respectively, and their zonal means are shown in Figure S7. Multi-model mean and across-model standard deviation of the net low and non-low cloud feedback components are shown in Table S2. Note that whereas the total low and total non-low cloud feedbacks sum to the total cloud feedback, one cannot add individual high and low cloud feedback components together to reproduce the standard equivalent (e.g., summing the non-low and low cloud amount feedbacks does not reproduce the standard cloud amount feedback).

The refined decomposition clearly distinguishes between the three net cloud feedbacks that are robustly nonzero and the remaining net cloud feedbacks that are closely constrained to be near zero.

4.1. Robustly Nonzero Net Cloud Feedback Components

In all models, net non-low cloud altitude and net low cloud amount feedbacks are robustly positive and net low cloud optical depth feedbacks are robustly negative (Figure 1b and c, black symbols). All three robustly nonzero net cloud feedbacks are characterized by feedbacks that operate nearly exclusively in one band (i.e., LW or SW), with little compensation from the other band.

The low cloud amount feedback has a larger multi-model mean, 0.35 $Wm^{-2}K^{-1}$, and greater inter-model spread, 0.20 $Wm^{-2}K^{-1}$ (1σ), than any other low or non-low feedback component. The ensemble mean net low cloud amount feedback is positive nearly everywhere, with the largest positive values in the low cloud regimes of the eastern ocean basins, over the cold tongue of the Eastern equatorial Pacific, and on the equatorward side of the storm tracks in either hemisphere (Figure 2f). The low cloud feedback over the equatorial Pacific cold tongue has been shown to be important for linking interannual and long-term cloud feedbacks [*Zhou et al.*, 2015].

There are two reasons why the net low cloud amount feedback is larger than the standard net cloud amount feedback. First, whereas the standard amount feedback is proportional to changes in total cloud fraction that are often the small residual of opposing non-low and low cloud fraction changes, the low cloud amount feedback is proportional to changes in only the low cloud bins, which generally exhibit changes of the same sign. Second, even if *only* low cloud fraction changed and there were no compensating changes in non-low cloud fraction, the standard net cloud feedback would be smaller because the standard decomposition "spreads" the cloud fraction decrease among all cloud types in proportion to their climatological abundance. Artificial reductions in high clouds (with net radiative effects that are weaker or of opposite sign) would accompany actual reductions in low level clouds, thereby reducing the net radiative impact. The larger the climatological coverage of high clouds relative to low clouds, the greater the artificial compensation between the negative LW cloud amount feedback and the positive SW cloud amount feedback in this scenario. Please see Supporting Information Section 2.2 for further discussion of ambiguities in the standard net cloud amount feedback, and the benefits of refining the decomposition.

Whereas the standard net cloud altitude feedback is large (0.32 $\mathrm{Wm^{-2}K^{-1}}$) and exhibits substantial inter-model spread (standard deviation of 0.14 $\mathrm{Wm^{-2}K^{-1}}$), the net non-low cloud altitude feedback is 63% as large (0.20 $\mathrm{Wm^{-2}K^{-1}}$) and exhibits 64% as much inter-model spread (standard deviation of 0.09 $\mathrm{Wm^{-2}K^{-1}}$). The reason for this is that changes in low cloud fraction are no longer allowed to exert any influence on the altitude feedback, and the resulting feedback quantifies only the feedback from changes in the altitude of free tropospheric clouds (for details, see Supporting Information Section 2.1). As expected [*Hartmann and Larson*, 2002; *Zelinka and Hartmann*, 2010], the non-low cloud altitude feedback is robustly positive across models. Notably, it is more spatially homogeneous than its standard counterpart (c.f. Figure 2g versus h), though it still has substantial spatial structure that is related primarily to the climatological abundance of high clouds.

The low cloud optical depth feedback is negative in all models, and is most prominent at middle to high latitudes in both hemispheres (Figure 2l). This large negative feedback is the primary reason that the total net cloud feedback is negative in these regions (cf. Figure 2a,l). All models exhibit increasing low cloud optical depth in the region of persistent mixed phase clouds over the Southern Ocean, likely due to warming-induced transitions from ice- to liquid-dominated clouds [*Tsushima et al.*, 2006; *McCoy et al.*, 2015; *Tan et al.*, 2016; *Ceppi et al.*, 2016a] and increases in adiabatic water content, which are more pronounced at cold temperatures [*Betts and Harshvardan*, 1987; *Somerville and Remer*, 1984].

4.2. Robustly Near-Zero Net Cloud Feedback Components

Net non-low cloud amount and optical depth feedbacks, low cloud altitude feedbacks, and residual feedbacks are very close to zero in all models, for reasons that make physical sense: First, low cloud altitude changes little, and would have a small effect on LW radiation even if it did. Second, LW and SW radiative effects of the ensemble of free tropospheric clouds closely cancel [*Kiehl*, 1994; *Hartmann et al.*, 2001], so changes in their coverage holding their altitude and optical depth fixed should result in a near-zero net amount feedback. Similarly, increases in cloud optical depth of free tropospheric clouds will lead to increases in SW reflection from greater cloud albedo that will be offset by decreases in outgoing LW radiation from greater cloud emissivity. This offset requires that free tropospheric clouds are sufficiently thin that an increase in their optical depth still leads to an increase in emissivity, as the LW effect saturates with increasing optical depth [*Ackerman et al.*, 1988].

4.3. Sources of Inter-model Spread in Net Cloud Feedback

Inter-model differences in equilibrium climate sensitivity (ECS) are driven by differences in net cloud feedback [*Dufresne and Bony*, 2008; *Caldwell et al.*, 2016], so it is important to understand the sources of inter-model spread in cloud feedback. To do so, we decompose the variance in net cloud feedback as a sum of variances in individual cloud feedback components and their covariances with each other (Figure 3). As in *Caldwell et al.* [2016], we plot only the terms of each covariance matrix that lie on or below the diagonal. The diagonal terms are the variance components, while those that lie below the diagonal are the covariance terms, which we multiply by 2. We normalize each matrix by the total variance in net cloud feedback, 0.07 $(\mathrm{Wm^{-2}K^{-1}})^2$, and express the contributors to the variance in percentage units.

Taken alone, low and non-low clouds each contribute roughly 40% to the inter-model spread in net cloud feedback (Figure 3a). Assuming their substantial covariance contribution of +19% is split evenly between them, then low and non-low cloud feedbacks are equally important (50% contribution each) in driving the spread in net cloud feedback. This result may seem surprising given the oft-cited dominant role of low clouds in driving uncertainty in cloud feedback.

This apparent discrepancy can be understood by further decomposing the spread due to low and non-low cloud feedbacks into their amount, altitude, and optical depth components (Figure 3b). Doing so confirms that the low cloud amount feedback is by far the dominant contributor to inter-model variance in net cloud feedback, accounting for 56.6% of the total variance. Although the low cloud optical depth feedback contributes very little to the inter-model spread in net cloud feedback, its anti-correlation with the low cloud amount feedback (r=-0.52) substantially reduces inter-model spread in net cloud feedback and weakens the overall role of low clouds in driving this spread. *McCoy et al.* [2016] suggest that this anti-correlation may be a result of model tuning rather than due to a physical linkage.

In contrast to the spread in net cloud feedback due to low clouds, that due to non-low clouds comes from relatively small variances in each component and from relatively small covariance terms that sum to a modest positive value (Figure 3b). These differences lead to nearly equivalent low and non-low net cloud feedback variances (Figure 3a).

The overall positive contribution to net cloud feedback variance from correlation between low and non-low cloud feedbacks (Figure 3a) arises almost entirely due to covariances between low cloud amount and non-low cloud feedback components (Figure 3b, bottom row). Covariance between low cloud amount feedback and both the non-low altitude and optical depth feedbacks increases spread in net cloud feedback. However, these covariances result from the large variance in low cloud amount feedback amplifying weak correlations with non-low altitude (r=0.32) and optical depth feedbacks (r=0.28). These weak correlations, coupled with the absence of a physical explanation for their existence, lead us to conclude that their positive contribution to spread is simply a random feature of this collection of models that may not be robust. In opposition to these positive covariances, a strong anti-correlation between low and non-low cloud amount feedbacks (r=-0.66) reduces spread in net cloud feedback. The net non-low cloud amount feedback is the small residual of LW and SW components and is essentially uncorrelated across models with non-low cloud fraction changes (r=-0.07). It is therefore unclear why this small residual is strongly anti-correlated with the low cloud amount feedback, and we caution that it may be entirely fortuitous. This strong anti-correlation does *not* indicate that models with larger decreases in low clouds tend to experience larger increases in non-low clouds or that this is a result of obscuration effects, since low and non-low cloud amount changes are actually weakly positively correlated across models (r=0.23). Understanding the mechanisms driving covariances among cloud feedback components and establishing their robustness are worthwhile topics of future research, given the quantitative importance of covariances for the ultimate spread in net cloud feedback and hence ECS.

4.4. Implications for Equilibrium Climate Sensitivity

Recently, *Stevens and Bony* [2013] derived a "null hypothesis" ECS of 2.7 K as that resulting from the sum of all feedbacks that they considered to be robust and well-understood: Planck, water vapor, lapse rate, surface albedo, and a "cloud-greenhouse feedback". In this section, we revisit this calculation taking into consideration our result that three nonzero net cloud feedback components are produced by all models and the results of a growing body of literature examining their robustness. Please see Supporting Information Section 3 for details of these calculations.

In addition to having a strong theoretical basis in the fixed anvil temperature (FAT) hypothesis [*Hartmann and Larson*, 2002], the tendency for tropical high clouds to rise nearly isothermally is also simulated in a global nonhydrostatic model [*Satoh et al.*, 2012; *Tsushima et al.*, 2014], cloud resolving models [*Tompkins and Craig*, 1999; *Harrop and Hartmann*, 2012], large eddy simulations [*Kuang and Hartmann*, 2007], and global simulations of radiative convective equilibrium [*Bony et al.*, 2016], and is supported by observational evidence [*Xu et al.*, 2007; *Eitzen et al.*, 2009; *Zelinka and Hartmann*, 2011]. This led *Stevens and Bony* [2013] to include a "cloud-greenhouse feedback" of 0.4 $Wm^{-2}K^{-1}$ in their calculation (B. Stevens, personal communication), which is equivalent to our standard LW cloud altitude feedback (Figure 1a). However, as we have demonstrated in this paper, the magnitude of the net (LW+SW) feedback due to the rise of free tropospheric cloud tops is 0.20 $Wm^{-2}K^{-1}$. Assuming all other robust feedbacks remain unchanged, this implies that null hypothesis ECS arising from the sum of well-understood feedbacks is actually 2.3 rather than 2.7 K. Note that this assumes that GCMs' non-low cloud altitude feedback magnitudes are correct, which requires that they simulate the correct climatological non-low cloud amount and emissivity and the correct upward shift of non-low clouds. This assumption is under current investigation.

Increasing evidence supports the robustly-simulated positive low cloud amount feedback, although physical arguments for it are not as elegant as those for FAT. Notably, models that are best able to reproduce the observed sensitivity of low cloud fraction to environmental conditions at low and middle latitudes have been repeatedly shown to be those that simulate decreasing low cloud cover under global warming [*Clement et al.*, 2009; *Sherwood et al.*, 2014; *Qu et al.*, 2015; *Zhai et al.*, 2015; *Myers and Norris*, 2016; *Brient and Schneider*, 2016]. Moreover, high resolution models that explicitly simulate the important interactions between turbulence, convection, and clouds also produce low cloud reductions in response to warming [*Bretherton*, 2015]. In light of these studies, we argue that inclusion of the low cloud amount feedback in the null hypothesis ECS calculation is warranted. Including its multi-model mean value of 0.35 $Wm^{-2}K^{-1}$ (along with the revised non-low cloud altitude feedback) leads to a null hypothesis ECS of 3.0 K.

Despite the fact that a negative low cloud optical depth is simulated by all models analyzed in this study, there is strong evidence that models overstate the strength of this feedback. Specifically, analyses of the observed sensitivity of low cloud optical depth or liquid water path to temperature [*Gordon and Klein*, 2014; *Ceppi et al.*, 2016a, b; *Terai et al.*, 2016] as well as targeted model experiments with observationally constrained cloud phase [*Tan et al.*, 2016] conclude that the negative low cloud optical depth feedback is too strong in most models. *Terai et al.* [2016] and *Tan et al.* [2016] suggest that the feedback should in fact be positive. Therefore we do not include the negative low cloud optical depth feedback in the revised null ECS calculation.

Finally, we note three caveats, which all indicate that 3.0 K may be an underestimate. First, using non-cloud feedback values from *Caldwell et al.* [2016] instead of from *Stevens and Bony* [2013] leads to a null hypothesis ECS of 3.2 K rather than 3.0 K (see Supporting Information). Second, the nonlinear dependence of ECS on feedback [*Roe and Baker*, 2007] implies that the average ECS of an ensemble of models is greater than the ECS estimated using the ensemble average forcing and feedback as is done here. Third, the ECS values derived here are likely an underestimate of the actual equilibrium temperature change following a doubling of CO_2, owing to the robust tendency for the net feedback to weaken as equilibrium is approached [*Gregory et al.*, 2004; *Armour et al.*, 2013; *Block and Mauritsen*, 2013; *Geoffroy et al.*, 2013; *Andrews et al.*, 2015].

4.5. Limitations

Although separately considering clouds above and below 680 hPa is sensible for many purposes, it can be misleading in regions that experience large changes in mid-level clouds. An increase in mid-level clouds contributes negatively to the non-low cloud altitude feedback, though this only occurs in MIROC5. Performing the decomposition over the conventional ISCCP high, mid-level, and low cloud classifications will avoid this problem, but at the expense of having a greater number of feedbacks to account for, which may make it more difficult to extract physically coherent patterns.

Additionally, one may question whether 680 hPa is the most appropriate cut-off for characterizing non-low cloud feedbacks, since physical interpretation of feedbacks due to clouds above the boundary layer may suffer from some of the ambiguities plaguing the standard decomposition discussed above. Using a 440 hPa threshold could be useful for focusing on purely high cloud feedbacks in the Tropics. However, the "high cloud mode" resides at lower altitudes at middle and high latitudes and its upward shift is better captured with a threshold at lower altitudes. Using a 560 hPa threshold may be a good compromise between the two, and in practice the results for the 560 and 680 hPa thresholds are qualitatively the same, as the feedback contributed by clouds in the $560 < CTP \leq 680$ hPa bin is very small (not shown). The optimal decomposition likely depends on the specific task at hand, and is best utilized in concert with the decomposition by individual cloud types [*Zelinka et al.*, 2012a].

5. Discussion and Conclusions

Fundamentally, the ambiguities in the standard decomposition of cloud feedback into amount, altitude, and optical depth components arise because changes in the entire population of clouds are considered collectively despite the fact that changes in gross cloud properties may not represent or be governed by a single physical process. The collective nature of the decomposition allows a cloud change that is confined to a specific region of $CTP-\tau$ space to manifest itself throughout the distribution, often in regions with vastly different radiative effects. Additionally, it allows large but compensating changes in clouds in widely-separated regions of $CTP-\tau$ space to manifest as zero cloud amount feedback but large altitude or optical depth feedbacks. By treating free tropospheric and low clouds separately, the refined decomposition largely circumvents these issues.

It is worth noting that the issues pointed out in this study with the standard decomposition are related to *interpretation* of the feedbacks, not to their quantification. For example, a reduction in only low clouds with no change in high clouds does technically result in increased cloud altitude when all cloud types are considered. It is only when one interprets the cloud altitude feedback as being solely due to FAT that one can be misled as to the strength and uncertainty of the actual feedback from rising high clouds. Indeed, we find that both the magnitude and inter-model standard deviation of the free tropospheric cloud altitude feedback is roughly 60% as large as that of the standard cloud altitude feedback because it excludes the aliasing effects of low cloud changes.

Despite the presence of large inter-model spread in cloud feedback, the refined decomposition reveals that the models are rather consistent in that they all produce – in the global mean – positive free tropospheric cloud altitude feedbacks, positive low cloud amount feedbacks, and negative low cloud optical depth feedbacks. All other net cloud feedbacks are strongly constrained to be near zero. Several lines of evidence support positive non-low cloud altitude and low cloud amount feedbacks and indicate that the negative low cloud optical depth feedback is overstated in models. Accounting for the two well-supported and robustly-simulated nonzero cloud feedbacks implies a null hypothesis ECS of at least 3 K.

Inter-model spread in net cloud feedback – which drives the spread in climate sensitivity – comes primarily from spread in net low cloud amount feedback. Whereas both the non-low cloud amount and low cloud optical depth feedbacks, in isolation, contribute very little to the inter-model spread in net cloud feedback, their strong anti-correlations with the low cloud amount feedback substantially reduce inter-model spread in net cloud feedback. To the extent that these large anti-correlations are fortuitous or artifacts of model tuning [*McCoy et al.*, 2016], spread in net cloud feedback may be spuriously small. Future work should evaluate the mechanisms that lead to covariances among cloud feedback components, given their important role in determining the ultimate inter-model spread in net cloud feedback and hence climate sensitivity.

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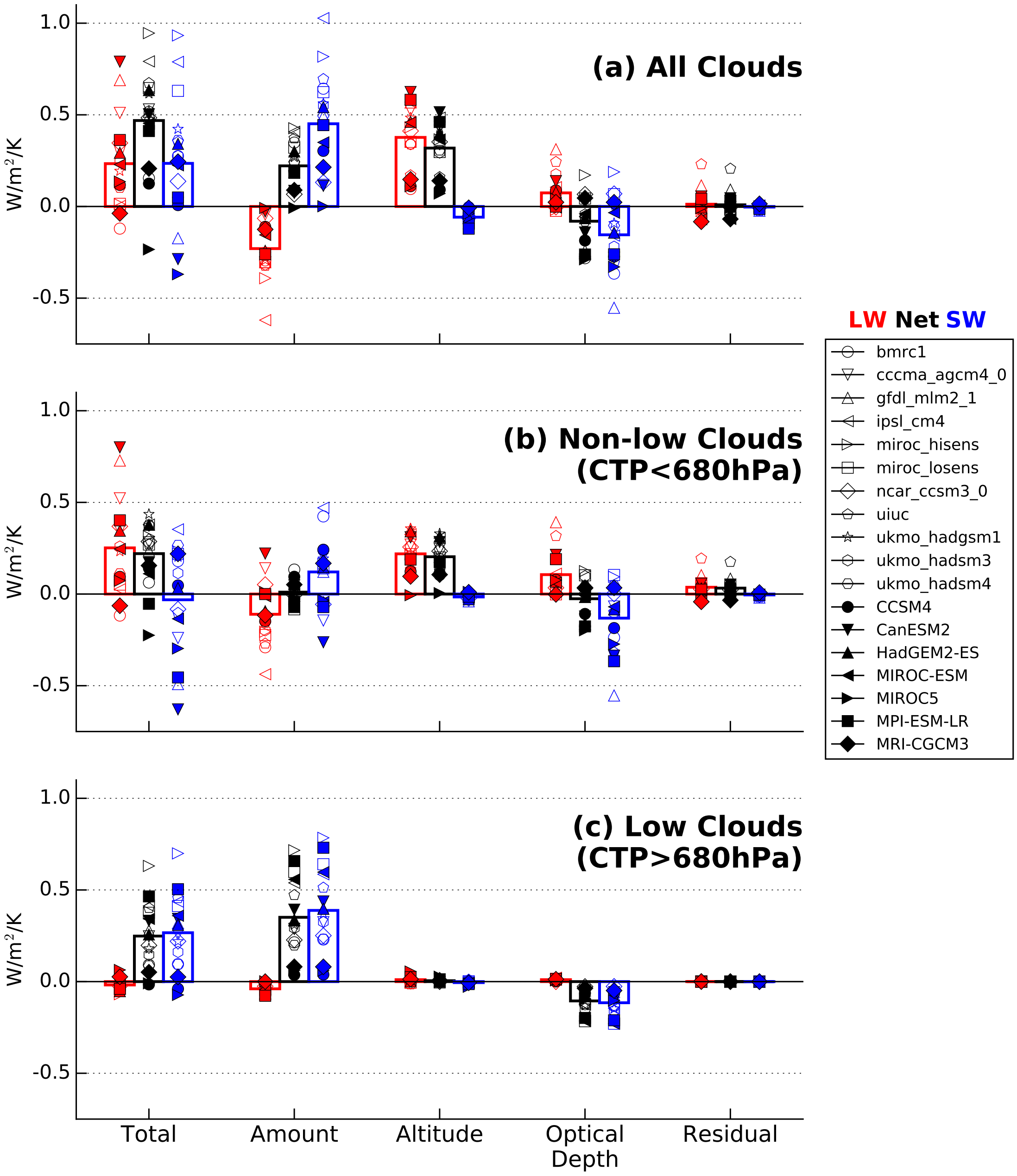

Figure 1. Global mean (red) LW, (blue) SW, and (black) net cloud feedbacks decomposed into amount, altitude, optical depth and residual components for (a) all clouds, (b) non-low clouds only, and (c) low clouds only. Open symbols are for CFMIP1 models and filled symbols are for CFMIP2 models. Multi-model mean feedbacks are shown as bars. Note that whereas the sum of low and non-low cloud feedbacks is equivalent to the total cloud feedback, one cannot recover the standard amount, altitude, and optical depth feedbacks shown in (a) by summing their low and non-low components shown in (b) and (c).

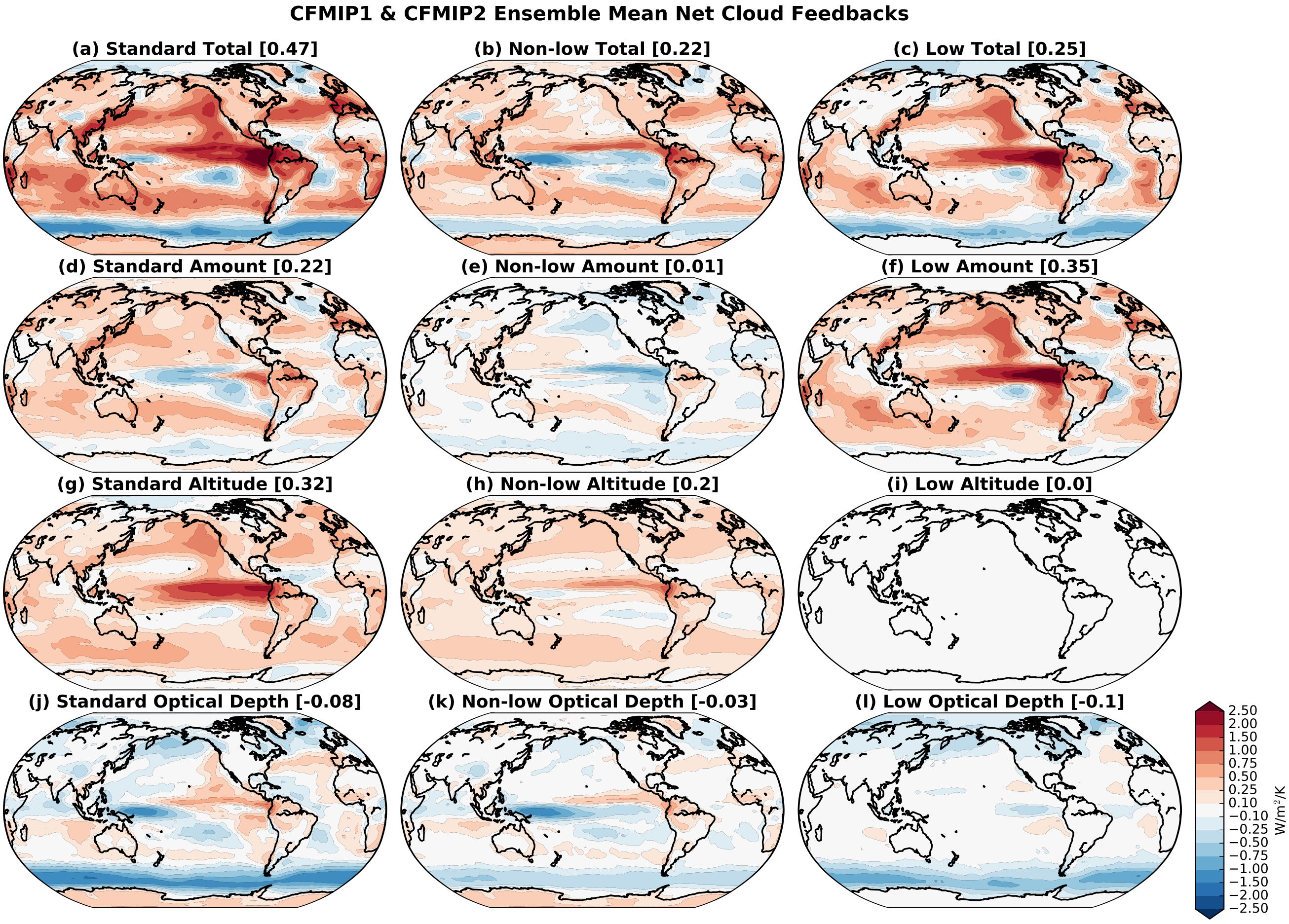

Figure 2. Multi-model mean net cloud feedback and its breakdown into amount, altitude, and optical depth components. Decompositions are computed using all clouds (left column), only free tropospheric clouds with CTP ≤680 hPa (middle column), and only low clouds with CTP >680 hPa (right column). Global mean values (in Wm^{-2}K^{-1}) are shown in brackets in the title of each panel.

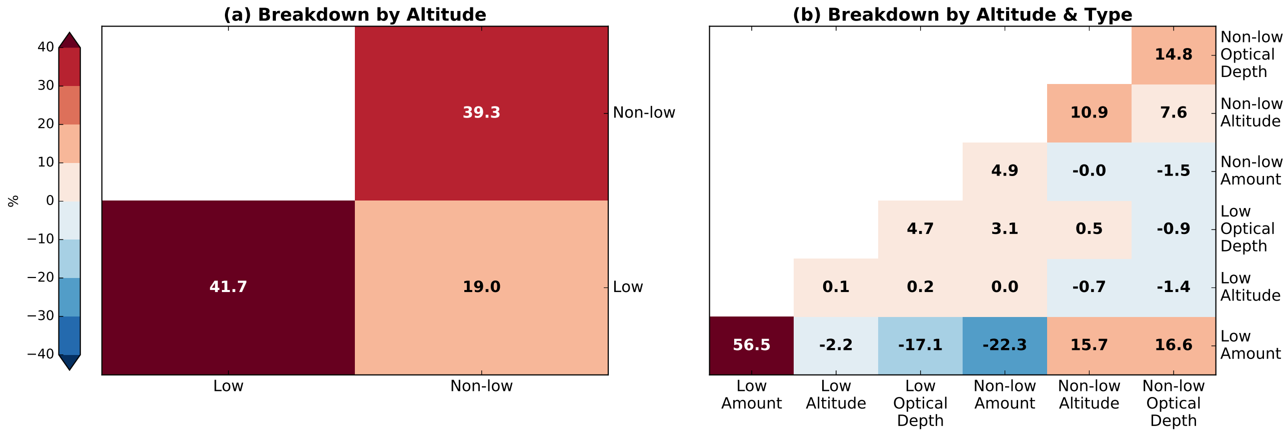

Figure 3. Fractional contributors to the inter-model variance in net cloud feedback, separated by (a) altitude and (b) both altitude and type. The total variance in net cloud feedback is 0.07 $(\mathrm{Wm}^{-2}\mathrm{K}^{-1})^2$. The sum of all elements in (b) is less than 100% because the residual feedback terms are omitted for clarity.