A Review of Controls on Tropical Deep Convecting Clouds

Course-Track Master's of Science Seminar Paper

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The response of clouds to warming has long been the greatest source of uncertainty in estimating climate sensitivity - or the response of the climate system to an external forcing (IPCC, 2013). The net cloud feedback is estimated to be positive, but there is large uncertainty (e.g., Ceppi et al., 2017). The SW cloud feedback, in particular, has a wide spread in both sign and magnitude in the CMIP5 ensemble (Figure 1 of Ceppi et al., 2017), which are associated with the uncertainty in the changes in low-level clouds (e.g., Sherwood, 2014; Ceppi et al. 2017 and references therein). The LW cloud feedback, however, is positive across the ensemble, suggesting that it is a primary factor providing a net positive cloud feedback. High clouds contribute to this positive LW cloud feedback (e.g., Ceppi et al. 2017; Hartmann and Larson 2002; Zelinka and Hartmann 2010; and Bony et al. 2016), however, despite the overwhelmingly positive sign, there is still a large spread in the magnitude. There have been increased attempts to understand the underlying mechanism controlling the properties of tropical anvil clouds in order to elucidate the differences and considerable variability in simulated cloud properties and their respective feedbacks in various models (Bony et al., 2015).

This paper will review the previous work accomplished with respect to the importance of high clouds in the climate system, the response of high clouds to warming surface temperatures, the hypotheses governing the systematic control of high cloud properties, and implications for climate sensitivity. Ultimately, this will serve as a component of the literature review for a paper in progress as well as a major portion of the Ph.D. dissertation work.

Introduction

High clouds associated with tropical deep convection, in both idealized models (Bony et al 2016) and with evidence from observations (Lindzen et al., 2001; Igel et al., 2014; Zelinka and Hartmann, 2011), reduce in coverage with surface warming. Lindzen et al. (2001), in particular, analyzed observations over the tropical ocean (weighted to account for the drastic difference in timescales of convection and SST changes) and found that the coverage of high clouds decreased substantially (upwards of 20%) with every 1K increase in SST. This result motivated analysis of this decrease's impact on climate sensitivity through idealized simulations of the tropical climate, a method that has since been used to frequently explore this problem.

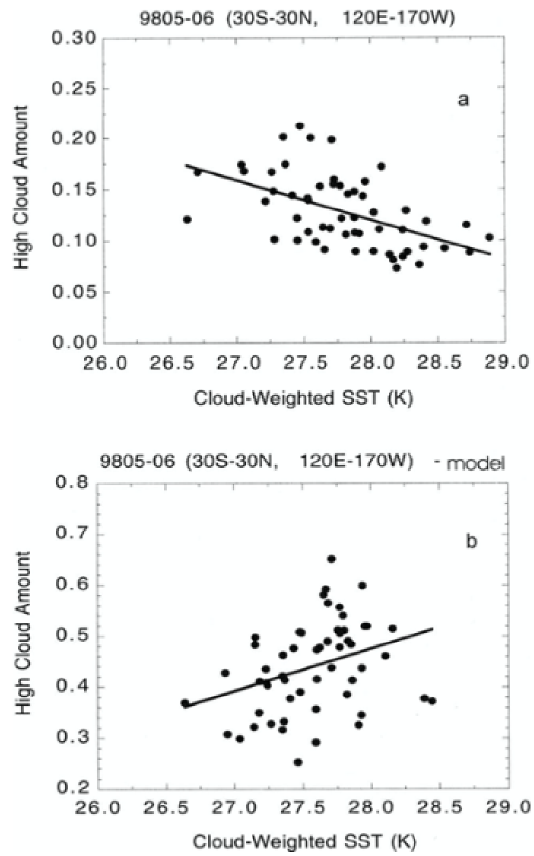

Figure 1: Figure 11 from Lindzen et al. (2001). The top panel plots high cloud coverage against SST from observations while the bottom panel shows the results from the model analysis.

They found that the response of high clouds to warming SST led to a negative climate feedback giving way to their hypothesis on the mechanistic impact of high clouds to Earth's climate sensitivity, the "infrared adaptive iris". When the clouds decrease in coverage, outgoing longwave radiation (OLR) more effectively cools to space effectively slowing, or even neutralizing, surface warming. Like the control of light received to the eye by its iris, clouds act to "open" and "close" the release of infrared radiation based on the changing sea surface temperature.

Although I use Lindzen et al. (2001) as motivation, it must be cautioned that it has since been highly criticized. Their proposition that in a warmer climate, enhanced precipitation efficiency via a microphysical mechanism will lead to less cloud being detrained into the troposphere from convection, has no physical basis. They also discuss the decreasing cloud cover resulting in a strong negative feedback, which is not necessarily the case (discussed further below). Later studies after showed that there were major issues in the "evidence" presented (e.g., Hartmann and Michelsen, 2002; Lin et al., 2002; Lin et al., 2004; Su et al., 2008).

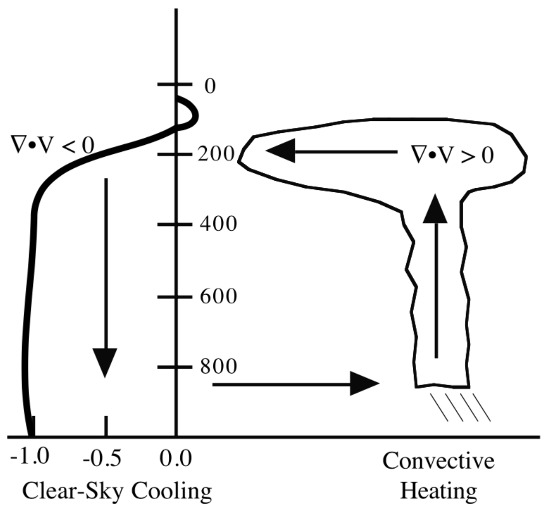

Figure 2: Figure 1 from Hartmann and Larson (2002) depicting the circulation of a system in RCE.

The GCMs studied by Lindzen et al. (2001) represent a reduction in cloud amount (see Figure 1) and, as such, they argued that impacts on the feedbacks due to the reduction in the cloud top were missing from climate projections. This further emphasizes the importance of correctly understanding and resolving the role of clouds.

The cloud feedback, however, is not necessarily negative in the net. As discussed by Bony et al. (2016), changes in high cloud amount could result in a negative feedback due to various mechanisms but it is not negative enough to change the sign of the overall cloud feedback. Bony et al. (2016) propose that this may be due to a reduction in high cloud coverage allowing for the positive effects of low cloud processes to be "felt" more by the climate system, resulting in a slight reduction of the overall positive cloud feedback but not a change in the sign. This motivates continued investigation into mechanisms for the changes in tropical deep convective clouds with warming and the contribution of clouds to climate feedbacks.

RCE and RCEMIP

Throughout this paper, "RCEMIP" will refer to the project description of Wing et al. (2018) and the first round of results of the project found in Wing et al. (2020). The Radiative-Convective Equilibrium Model Intercomparison Project, RCEMIP, consists of over 30 models including Cloud Resolving Models (CRMs), General Circulation Models (GCMs), Global Cloud Resolving Models (GCRMs), and Large Eddy Simulations (LES). These models are all consistently configured as idealized simulations (e.g. aquaplanet, uniform insolation, uniform SST, no rotation) of radiative-convective equilibrium (RCE), which is where, on average, radiative cooling balances convective heating and is a simplified view of the tropical atmosphere. The simulations are run at three different SSTs (295K, 300K, and 305K) to simulate different climates and on a "large" domain size that allows for organized convection to occur as well as a "small" domain that resists organization of convection.

A frequent diagnostic that will be referred to throughout this paper is the cloud fraction and the cloud anvil. In RCEMIP, cloud fraction is defined as a grid point with cloud condensation values greater than 1x10^{-5} g g^{-1}, or 1% of the saturation mixing ratio over water, whichever is smaller, or the output of a cloud

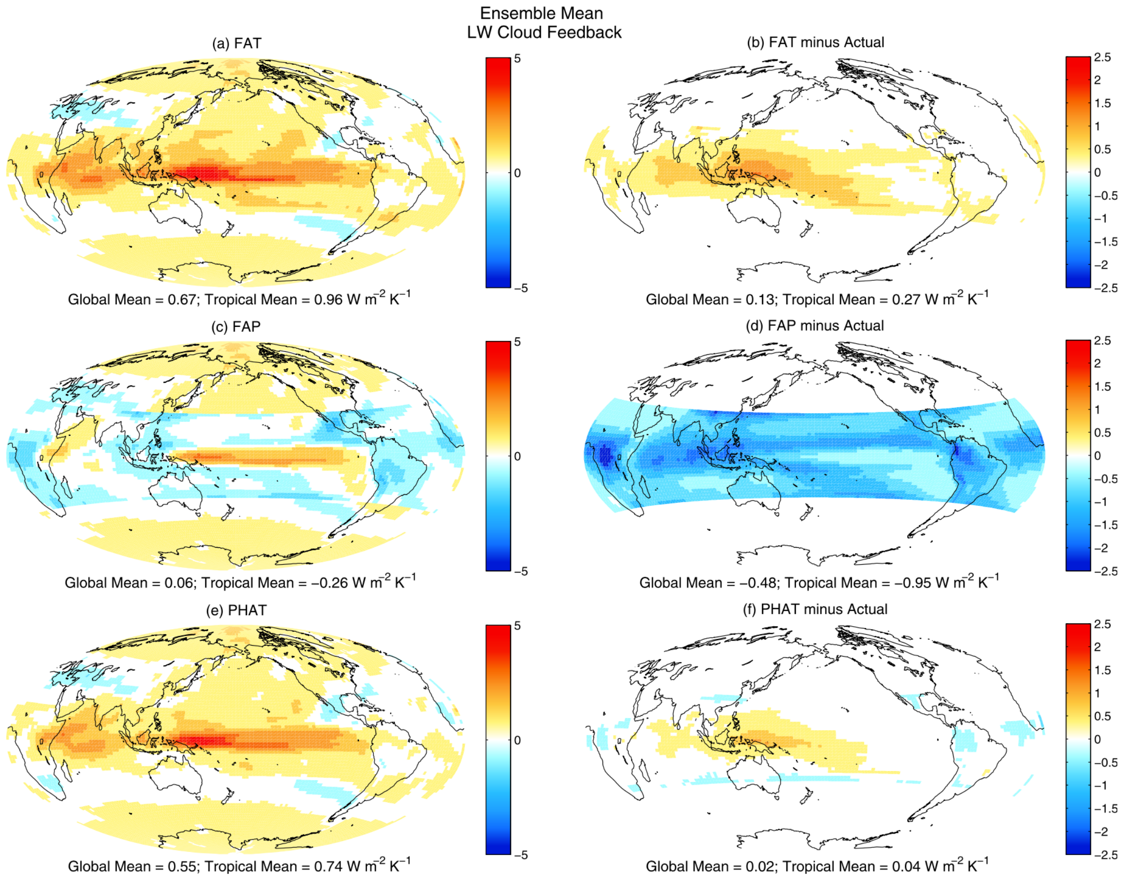

Figure 3: Figure 11 from Zelinka and Hartmann (2010) showing the LW cloud feedback for FAT, FAP, and PHAT (a,c,e) as well as their difference from the actual LW cloud feedback calculated from the models (b,d,f).

scheme, if enabled in the model. The cloud anvil is the upper level maximum in cloud fraction.

FAT, PHAT, or FAP

As described by Hartmann and Larson (2002), motivating an often cited hypothesis for a constraint on anvil properties, from an RCE perspective, convection removes instabilities created by temperature tendencies from radiative cooling convection is thus constrained to the regions of efficient radiative cooling (e.g. the troposphere). They go on to propose that the temperature of the anvil remains fixed as the surface temperature changes. This arises from a simple thermodynamic constraint on the radiative cooling profile (emission in the upper troposphere primarily coming from water vapor, with water vapor content being controlled by the Clausius-Clapeyron relationship). As depicted in Figure 2, radiative cooling times drop off because of the reduced ability of water vapor to radiate away temperature, causing net warming above this "radiative tropopause" (Zelinka and Hartmann, 2010). This causes the cooling rates to fall to zero at a much lower height than the cold point tropopause. Since the radiative cooling profile is thermodynamically constrained, so then will be the temperature of anvil clouds. The mass divergence from convective clouds supplies the necessary mass convergence and subsidence needed to offset radiative cooling in the clear-sky regions with adiabatic warming from subsidence. This idea that the temperature of convective anvils remains constant is referred to as the "Fixed Anvil Temperature" hypothesis, or FAT.

Zelinka and Hartmann (2010) expanded FAT to be a part of a continuum of sorts for the possible scenarios determining the longwave cloud feedback. FAT is one extreme while the other is a fixed anvil pressure (FAP) scenario. The middle ground is characterized by a proportionately higher anvil temperature (PHAT) scenario. Using decadal means from 2000-2010, 2060-2070, and 2090-2100 from the IPCC CFMIP SRES A2 scenario simulations, they calculated the longwave cloud feedback as well as decomposed the feedback into the hypothetical FAT, FAP, and PHAT scenarios for the tropics. Their results are shown in Figure 3. They find that in a FAP scenario, where high clouds remain at a constant pressure rather than shifting to lower pressures with warming temperatures, the temperature of the high clouds greatly increases, drastically altering the OLR resulting in a negative longwave cloud feedback (Figure 3d). When the system follows FAT (Figure 3a-b), the feedback is a large positive and greater than what the actual feedback is.

Earlier in Zelinka and Hartmann (2010) they showed the changing behavior in profiles of specific humidity, temperature, radiative cooling, static stability, diabatic vertical motion, and diabatic convergence; diagnostics that show the thermodynamic constraint on anvil properties similar to what was discussed earlier. Specifically, they found that static stability increases in the upper troposphere with a warming temperature profile (Figure 3 in Zelinka and Hartmann (2010), not shown). In a PHAT scenario (Figure 3e), anvils will experience a slight increase in temperature owing to the increase in static stability in a warmer climate and is accompanied by a feedback smaller than FAT but still positive since the clouds only slightly warm (unlike FAP). Figure 3f shows that PHAT agrees with the feedback calculated from the model data much better than the other two scenarios, especially more so than FAP. More importantly, the relationship has sound physical reasoning supporting it.

Cloud changes in RCEMIP

Indeed, FAT or PHAT is a frequent result in RCE studies and observations alike (e.g. Huang and Hartmann, 2007; Zelinka and Hartmann, 2010, 2011; Cronin and Wing, 2017; and references therein). In RCEMIP, we found that the majority of the models followed the PHAT hypothesis where the anvil temperatures increased, on average, 4.4K over the 10K SST range (Figure 4, right panel). There are a few models in RCEMIP that have a surprising decrease in anvil temperature with warming SST. We suspect the current method for

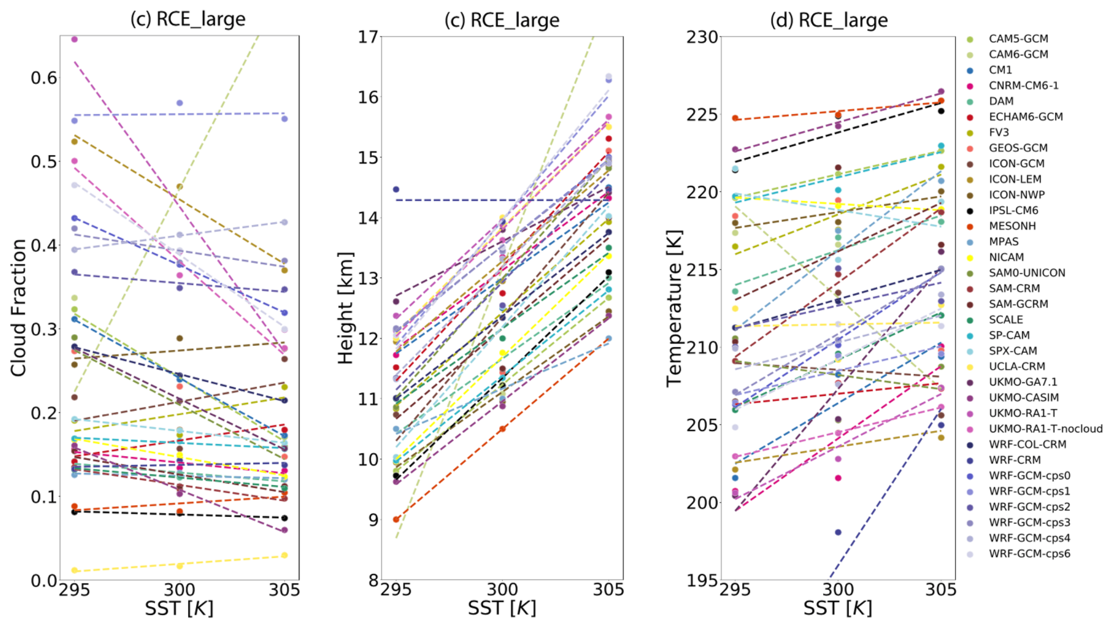

Figure 4: Figure 15 (left panel) and 14c-d (middle and right panel) from Wing et al. (2020) showing the cloud fraction, height, and temperature of the anvil (at the altitude of the upper-level maximum in cloud fraction) for large domain models that allow for aggregated convection to occur.

diagnosing the anvil may not be consistent with the way the level of mass divergence or radiative cooling may be diagnosed, suggesting the need for a better diagnostic metric of the convective anvil, something we hope to explore going forward. The value of cloud fraction itself my be incorrect where the threshold used in RCEMIP may be too small and, therefore, flagging grids as clouds that may not be clouds. This necessitates the need for a higher threshold.

RCEMIP also found that the anvil height increases with warming across the models (Figure 4, middle panel), independent of domain size (and thus, independent of whether the convection aggregates or not). The average increase in height with warming SST is larger for the large, aggregated, domains at 0.3 km K^{-1}. The small domain simulations average a 0.2 km K^{-1} increase with a larger percentage of models falling below the average than the large domain. We found that anvil cloud height in 70% of the models increases at a faster rate with warming, indicated by the increase in anvil height being larger from the 300K to 305K simulations than the increase from 295K to 300K.

The anvil cloud fraction (Figure 4, left panel) has less consistent behavior across the models. The majority (70%), however, decrease with warming from 295K-305K. Those that have an increase in cloud fraction with warming tend to do so non-monotonically where there is a decrease from 295K to 300K but either remains steady or increases from 300K to 305K. Even when the cloud fraction decreases from 295K to 305K, the individual change from 300K to 305K tends to be much smaller than that from 295K to 300K. Bony et al. (2016) suggests there may be a limit to how small the cloud fraction can get, which we may be seeing something along the same lines in the RCEMIP results and hope to explore further as our work continues.

Alternative to the FAT/PHAT hypotheses

Recently, the underlying assumptions in FAT and PHAT have been reexamined. In a pair of papers (Seeley et al. 2019a,b), the physics governing anvil clouds are analyzed and the underlying assumptions leading to the FAT argument are judged for the effectiveness of their reasoning. In Seeley et al. (2019a) they propose that the position of the anvil cloud is controlled by a microphysical lifetime as opposed to a radiatively-driven peak in convective mass divergence. Upper tropospheric cloud condensate particles have a long lifetime so clouds that form there stay longer. Cronin and Wing (2017) discussed that this microphysical lifetime mechanism is difficult to show and compare to the mass convergence mechanism using model output. That said, RCEMIP does seem to support PHAT (Wing et al. 2020) and, similarly, Seeley et al. (2019a,b) found that the anvil temperatures are not fixed, violating the FAT hypothesis. Instead, their simulations followed a Fixed Tropopause Temperature, or FiTT, where the tropopause is radiatively-defined. If the tropopause temperature is fixed, the anvil temperature cannot automatically be assumed to be fixed.

Radiatively-driven divergence

Bony et al. (2016) review the efforts made to understand why high cloud amount would decrease with warming, a result that is consistent but does not yet have a robust physical understanding as the result of isothermally (or near-isothermally) rising cloud tops does. They then propose that the mechanisms controlling anvil coverage are the same that control cloud top height and temperature, reviewed earlier.

As in Hartmann and Larson (2002), Bony et al. (2016) investigate anvil coverage use the peak of radiatively-driven divergence (R_D, Figure 2) where the height of the peak in R_D corresponds closely to where the anvil cloud is located. R_D is calculated from clear-sky radiative cooling (Q_r) and static stability (S); $R_D = \frac{\partial \omega}{\partial P}$ where $\omega = -\frac{Q_r}{S}$ and $S = -\frac{T}{\Theta}\frac{\partial \Theta}{\partial P} = \left(\frac{R_D}{c_{pd}}\right)\frac{T}{P}(1-\gamma)$. Figure 6 shows that anvil cloud fraction and R_D decrease nearly together with warming temperature. This relationship is found in both observations (Zelinka and Hartmann, 2011), CRMs (Cronin and Wing, 2017), and GCMs run in RCE (Bony et al., 2016, and Figure 6). Bony et al. (2016) also found these patterns in both aggregated and un-aggregated simulations as well as non-RCE states. This suggests this is a fundamental property of the relationship between anvil coverage and mass convergence.

Bony et al. (2016) demonstrate that this arises because, as the surface warms, isotherms rise to lower pressures and regions of higher static stability. In fact, they explain that static stability is required to

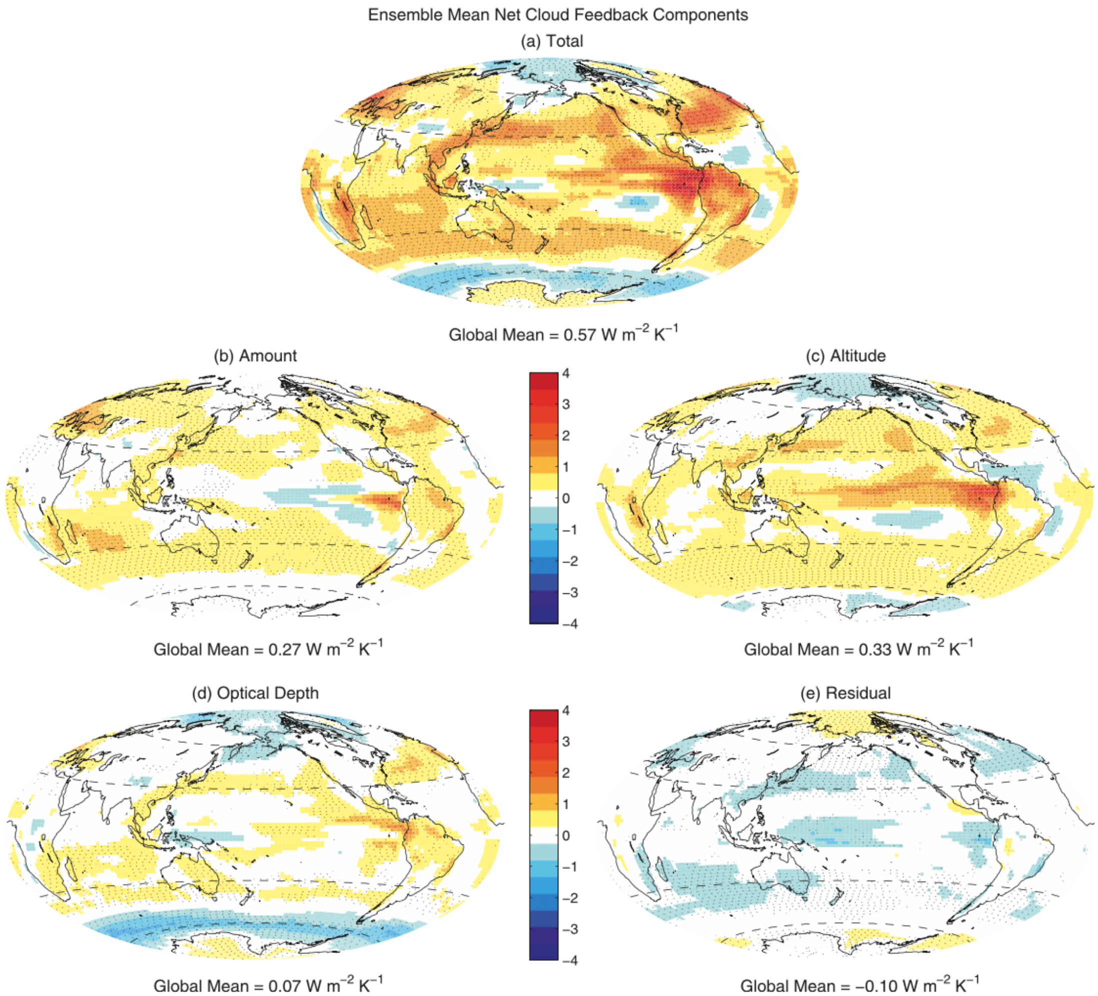

Figure 5: Figure 5 from Zelinka et al. (2012b) showing the total net feedback parameter (a) and the contributions to (a) from changing cloud amount (b), cloud vertical distribution (c), cloud optical depth distribution, and the residuals (e, not discussed).

increase to decrease the pressure necessary for a FAT scenario or increase the temperature necessary for a PHAT scenario. An increase in static stability means that less subsidence (and thus, R_D) is needed to balance radiative cooling. Therefore, anvil coverage decreases. This decrease in anvil coverage allows more longwave cooling to space and, thus, acts as a "stability iris". However, the stability iris mechanism is more robustly found and basic than that of the iris proposed by Lindzen et al. (2001). This mechanism from Bony et al. (2016) avoids the danger of being "missing" from models by not only having a theoretical basis but by having a theoretical basis that involves physics robustly represented in GCMs. This is a step up from the microphysical mechanism proposed in Lindzen et al. (2001) which has no solid supporting theory.

R_D defined physically from a basic thermodynamic relationship becomes even more important when the cloud feedback is analyzed from the inputs of various cloud properties. Using CFMIP1 models and a novel technique of partitioning the cloud feedbacks (discussed further in the next section) into contributions from anvil cloud fraction, altitude, and optical depth in isolation of one another, Zelinka et al. (2012b) found that the largest contributors to the net cloud feedback are from cloud amount and altitude (Figure 5). Specifically, they found that the altitude feedback contributes the most to the net cloud feedback, approximately 50% of the positive feedback. As emphasized by Zelinka et al. (2012b), a physical process (R_D) insensitive to model specifics controlling a large portion of the feedback (cloud height and amount) is important and adds confidence to conclusions drawn from the impact of changing cloud altitude to warming.

Partitioning clouds

Cloud feedbacks from changes in coverage of different cloud types

Throughout this paper cloud changes with warming have been focused on high clouds and, in particular, all high clouds. Expanding upon the earliest studies of the role of changing cloud altitude, amount, and optical thickness (e.g. Schneider and Dickinson, 1974; Schneider, 1972; Cess, 1974, 1975) Zelinka et al (2012a,b) look at the changes in clouds with warming based on specific cloud types by partitioning the clouds by cloud top pressure and optical depth. This also allowed them to look at what cloud types are responsible for the cloud feedbacks.

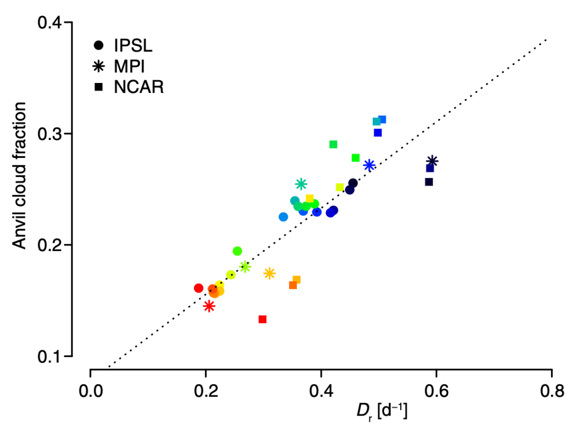

Figure 6: Figure 3 from Bony et al. (2016) showing the relationship between anvil cloud fraction and radiative-driven divergence for three models (the symbols) run in RCE at various SSTs (the colors, blue to red : cold to warm).

They do this by taking advantage of the availability of satellite measurements of cloud top pressure, cloud amount, and cloud optical depth, and the access of these quantities from model satellite simulators for use with radiative kernels. In general, radiative kernels are a tool that allows for the analysis of the sensitivity of radiative fluxes to perturbations of a property which is then used to define the impact of this property on radiative feedbacks. The properties that are typically perturbed are temperature and specific humidity (Soden et al., 2008). The difference between all-sky kernel and clear-sky kernel can be used to derive a correction factor that allows for a more accurate estimate of cloud feedbacks than simply using changes in cloud radiative forcing (Soden et al., 2008). Cronin and Wing (2017) proposed an approximate kernel methodology suitable for estimation of climate feedbacks

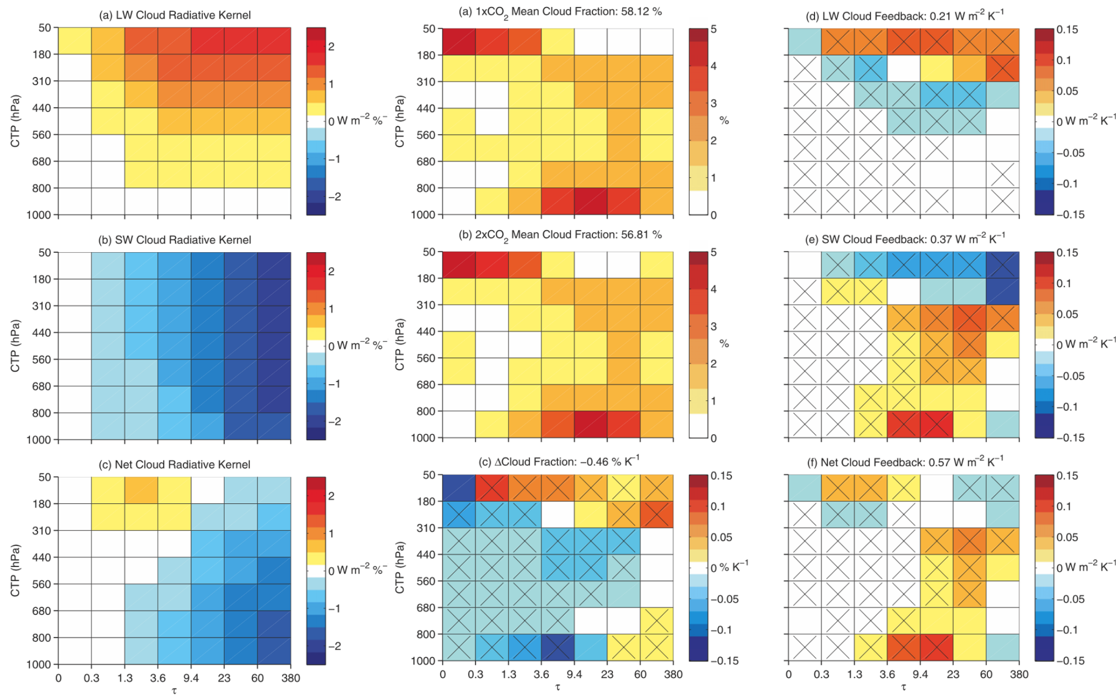

Figure 7: Figure 1 (left-most column) and 2 (middle and right-most column) from Zelinka et al. (2012a). The left column shows the radiative kernels calculated for each cloud type which is then multiplied by the change in cloud fraction between the two climates (the middle column, c) to get the cloud feedbacks for each cloud type shown in the right most column.

in RCE. In Zelinka et al. (2012a,b) they calculate cloud radiative kernels by perturbing cloud fraction in order to estimate cloud feedbacks, that is, the affect of cloud changes on LW, SW, and net radiative feedbacks. Radiative kernels may be computed for an alternate phase space in which these properties are viewed, an attribute Zelinka et al. (2012a,b) take advantage of to identify which types of clouds have an impact on radiative feedbacks when they change with a warming climate. As previously mentioned, we know that clouds have a significant impact on the climate system and that their change with warming is equally as important, but we are also aware that there is a diverse spectrum of clouds with different properties and those properties have different radiative effects. We want to know what these are and why they occur, which is why Zelinka et al. (2012a,b) use the radiative kernels to view the cloud changes from a cloud top pressure (CTP) versus optical depth vantage point.

Using the radiative kernel technique, Zelinka et al. (2012a) compute LW, SW, and Net cloud radiative kernels. They find that the LW kernel is positive everywhere (Figure 7, left column (a)), with stronger positive values for higher and thicker clouds. The SW radiative kernel (Figure 7, left column (b)) is negative everywhere with stronger negative values for thicker clouds. This means that increases in cloud fraction are associated with decreased OLR and increased SW reflection. The net result (Figure 7, left column (c)) is large negative values for thick and low clouds increasing as you go thinner and higher with a concentration of positive values for the highest clouds in the 0.3-9.4 range of optical thickness.

These kernels are then multiplied by the change in cloud fraction between a cooler and warmer climate (Figure 7, middle column (c)) to arrive at the LW, SW, and net cloud feedbacks, the impact of each cloud type on the radiative feedbacks. The LW cloud feedback (Figure 7, right column (d)) is heavily influenced by changes in cloud fraction at higher altitudes where increases in cloud fraction result in a positive LW feedback. The opposite occurs for the SW cloud feedback throughout the entire atmosphere, where increases in high cloud fraction result in a negative SW feedback and decreases in low cloud fraction result in a positive SW feedback. The SW feedback, whether negative or large, predominantly occurs at higher thicknesses with small thicknesses having a negligible effect. The resulting net cloud feedback is primarily influenced by the positive low-level SW feedback (since there is no LW cloud feedback in the lower levels) with competition between the LW and SW feedbacks in the upper levels where the SW dominates for thick clouds and the LW feedback dominates for the thinner clouds.

Cloud feedbacks from changes in the distribution of cloud types

Zelinka et al. (2012b) takes Zelinka et al. (2012a) a step further by calculating the cloud feedback due to clouds changing altitude or thickness as well as calculating the cloud feedback due to the relative cloud amount for a cloud type remaining constant despite cloud changes occurring. The process is similar to that above, a change in a property is multiplied by the cloud radiative kernels of Zelinka et al. (2012a) except this time, instead of calculating the total cloud feedback, the cloud amount, cloud altitude, and cloud optical depth (τ) feedbacks are calculated. They do this by decomposing the change in cloud fraction to isolate the changes in one property (total cloud fraction, altitude, or optical depth) from the contributions of changes from the other two. The amount feedback is computed from the ratio of the change in total cloud fraction to the total cloud fraction of the current climate multiplied by the current climate's cloud fraction matrix, $\Delta\mathbf{C}_{prop} = \left(\frac{\Delta C_{tot}}{C_{tot}}\right) \times \mathbf{C}$, which itself is multiplied by the radiative kernels to find the cloud amount feedback. The altitude feedback is computed by subtracting the mean anomaly (the sum terms in the following equations, where P and T are the total number of CTP and τ bins respectively) across CTP bins from each optical thickness bin of the anomalous cloud fraction histogram to isolate the change in vertical distribution, $\Delta\mathbf{C}_{\Delta p} = \Delta\mathbf{C} - \frac{1}{P}\sum_{p=1}^{P}\Delta\mathbf{C}$. Similarly, the optical thickness feedback is computed by subtracting the mean anomaly across optical thickness bins from each CTP bin of the anomalous cloud fraction histogram to isolate the change in vertical distribution, $\Delta\mathbf{C}_{\Delta p} = \Delta\mathbf{C} - \frac{1}{T}\sum_{\tau=1}^{T}\Delta\mathbf{C}$.

The net cloud feedback results of the partitioning are shown in Figure 5. As discussed previously, the majority of the net cloud feedback comes from decreasing CTP and decreasing cloud amount, with the CTP effect dominating and backed in physical reasoning (e.g. FAT/PHAT). The positive LW feedback (not shown) largely comes from the decrease in CTP with warming although 75% of its contribution is offset by a globally-robust negative LW feedback from decreasing cloud amount for reasons that are not fully understood, though this may be explained by the stability iris of Bony et al. (2016). The SW feedback (not shown) is dominated by the changes in cloud amount component (changes in cloud fraction when optical thickness and CTP are held constant). The CTP component is negligible and the optical depth feedback is negative where optical thickness increases and positive where it decreases.

Conclusion

In RCEMIP we find that high convecting tropical clouds generally, with varying degrees of spread, decrease in amount, increase in height, and increase in temperature with warming SSTs. The current hypothesis for controlling these behaviors supported by the RCEMIP models involves the stability iris of Bony et al. (2016) where clear-sky radiatively-driven mass convergence controls anvil height and causes the anvil to increase slightly in temperature. This results in RCEMIP following the PHAT hypothesis of Zelinka and Hartmann (2010) because the clouds find themselves in a more stable and therefore warmer environment, though the anvil clouds warm far less than they would if they were staying at fixed pressure.

In future work with RCEMIP, we hope to move from qualitative descriptions of the climates simulated by the models towards understanding why the changes observed occur. This will be done by using this unique dataset to test the theories reviewed in this paper across the hierarchy and diverse set of models, all of which are commonly configured. This bridges the gap between the various experimental designs of the past in order to see what are fundamental relationships and what may be artifacts of individual model design, requiring further understanding and/or tuning of parameters and schemes.

Using RCEMIP, we are testing the stability iris mechanism of Bony et al. (2016) by looking at how the elements that go into R_D change with respect to each other as well as in isolation of each other. The latter is accomplished by calculating R_D at 295K and 305K while one variable stays locked at our control temperature, 300K. We are also working on applying a kernel correction to the cloud feedback estimates calculated in Wing et al. (2020) in a similar manner to Cronin and Wing (2017). These cloud feedbacks will also be decomposed into cloud amount, altitude, and optical depth components, as in Zelinka et al. (2012a,b), which will, to our knowledge, be the first attempt to apply such a method to CRMs.

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