On the relationships among cloud cover, mixed-phase partitioning, and planetary albedo in GCMs

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Key Points:

• Cloud cover and mixed-phase parameterization compensate in GCMs.
• Models that maintain liquid to lower temperatures have less cloud cover.
• This compensation affects both the climate mean-state and cloud feedback.

Abstract

In this study it is shown that GCMs that fail to maintain supercooled liquid at lower temperatures tend to have a greater mean-state cloud fraction and more negative cloud feedback in the middle and high latitude Southern Hemisphere. We investigate possible reasons for these relationships by analyzing the mixed-phase parameterizations in 26 global climate models (GCMs). The atmospheric temperature where ice and liquid are equally prevalent (T5050) is used to describe the mixed-phase parameterization in each GCM. Liquid clouds have a higher albedo than ice clouds, so, all else being equal, models with more supercooled liquid water would also have a higher planetary albedo. The lower cloud fraction in these models compensates the higher cloud reflectivity and results in clouds that reflect a reasonable amount of shortwave radiation (SW), but gives
clouds that are too bright and too few. We know of no robust physical mechanism that
can be invoked to explain the anti-correlation between the temperature at which
supercooled liquid can remain unfrozen and cloud fraction in the climate mean state,
especially because this anti-correlation extends through the subtropics. A set of perturbed
physics simulations with the Community Atmospheric Model Version 4 (CAM4) shows
that, if its temperature-dependent phase partitioning is varied and the critical relative
humidity for cloud formation in each model run is also adjusted to bring reflected SW
into agreement with observations, then cloud fraction increases and liquid water path
(LWP) decreases with T5050, as in the CMIP5 ensemble.

1. Introduction

The low cloud response to warming remains one of the largest sources of
uncertainty in the representation of the overall climate feedback [Bony et al., 2006;
Dufresne and Bony, 2008; Vial et al., 2013; Webb et al., 2013; Zelinka et al., 2012;
Zelinka et al., 2013]. It is important to note that not only the change in the clouds with
warming relative to the control climate, but the control climate itself also modulates
climatic feedbacks in models [Grise et al., 2015; Trenberth and Fasullo, 2009].
Recent studies have identified several robust features of the low cloud feedback.

In the subtropics, low cloud cover decreases with warming, leading to a positive feedback
[Brient and Bony, 2013; Qu et al., 2014; Qu et al., 2015; Zelinka et al., 2012; Zelinka et
al., 2013]. This simulated response has been attributed to drying of the subtropical free
troposphere in response to changes in circulation [Senior and Mitchell, 1993; Sherwood
et al., 2014; Sherwood et al., 2010; Tsushima et al., 2006; Wright et al., 2010], although
observational studies and cloud resolving simulations suggest a variety of different mechanisms may lead to reduced subtropical cloud cover in a warming climate [Blossey et al., 2013; Bretherton and Blossey, 2014; Bretherton et al., 2013; Clement et al., 2009; Klein et al., 1995; McCoy et al., 2015a; Myers and Norris, 2013; 2014; Norris and Leovy, 1994; Qu et al., 2014; Qu et al., 2015]. In the midlatitudes the cloud feedback becomes robustly negative as cloud optical depth increases in step with warming [Zelinka et al., 2012; Zelinka et al., 2013]. The increase in cloud optical depth in this region has been attributed to transitions from relatively unreflective ice to relatively bright liquid condensate as the atmosphere warms [Ceppi et al., 2015; Choi et al., 2014; Gordon and Klein, 2014; Komurcu et al., 2014; McCoy et al., 2014a; McCoy et al., 2015c; Naud et al., 2006; Tsushima et al., 2006; Zelinka et al., 2012; Zelinka et al., 2013]. The treatment of mixed-phase clouds in GCMs is highly uncertain. McCoy et al. [2015c] showed that 19 GCMs from the Coupled Model Intercomparison Project phase 5 (CMIP5) effectively partition ice and liquid as a monotonic function of atmospheric temperature, even though some of the GCMs include prognostic mixed-phase cloud physics [Cesana et al., 2015; Komurcu et al., 2014]. This is corroborated by Cesana et al. [2015]. McCoy et al. [2015c] demonstrated that the temperature where ice and liquid were diagnosed to be equally prevalent (T5050) in the GCMs varied by up to 35 K in the 19 models surveyed. Across-model variations in T5050 were shown to determine a significant fraction of the across-model variations in LWP increases between the control climate and the RCP8.5 scenario in the Southern Ocean region. While disquieting from the perspective of constraining climate uncertainty, this is not inconsistent with the complexity of the processes that take place in mixed-phase clouds. Ice and liquid have
drastically different microphysical and radiative properties. Transitions between the two
states as dictated by nucleation, secondary ice formation, and the Bergeron-Findeisen
process remain poorly constrained observationally and in large-eddy simulations
[Atkinson et al., 2013; Cesana et al., 2015; Kanitz et al., 2011; Komurcu, 2015; Komurcu
et al., 2014; Korolev et al., 2003; Morrison et al., 2011; Murray et al., 2012].

Because of this lack of robust constraint on the processes that take place in mixed-
phase clouds, GCMs portray these processes in a wide variety of ways [Cesana et al.,
2015; Komurcu et al., 2014; McCoy et al., 2015c]. As has been shown, the partitioning of
ice and liquid in mixed-phase clouds exerts a significant control on cloud albedo [McCoy
et al., 2014a; b; McCoy et al., 2015c]. This allows the uncertainties in the mixed-phase
parameterization of a given model to significantly affect both the SW radiation that is
reflected in the climate mean-state and the change in reflected SW radiation with
warming.

In Section 2 we discuss the model data used in this study, the derivation of each
model’s T5050 parameter, and the observational data sets used to evaluate model
behavior. In Section 3 we will discuss the across-model dependence of the climate mean
state on each model’s mixed-phase parameterization. We will also discuss how
adjustments of climate models that are needed to make the resulting cloud radiative
effects agree with observations may depend on how the mixed phase processes are
parameterized. A set of perturbed physics runs in CAM4 will be used to support these
results. Finally, we will discuss how across-model variations in mixed-phase
parameterizations affect the cloud feedback.

2. Methods
GCMs have been shown to effectively partition ice and liquid in a given atmospheric volume as a monotonic function of atmospheric temperature, even if the GCM does not use a simple function of temperature to determine partitioning [Cesana et al., 2015; McCoy et al., 2015c]. We can characterize the curve of liquid to total condensate for each GCM in terms of the temperature where ice and liquid are equally prevalent, referred to as T5050. It should be noted that this characterization is relatively crude. Two GCMs can have very different curves describing their phase partitioning, but the same T5050. The midpoint of the curve describes the general position of the curve and provides a rough estimate of the temperatures at which supercooled liquid exists for a given model. Using the same techniques as McCoy et al. [2015c], we calculate T5050 for 26 GCMs from the CMIP5 archive using the latitude band from 30°S-70°S (Figure 1a). This yields 26 T5050s, one to describe each of the 26 GCMs (Table 1).

The 30°S-70°S latitude band in the Southern Ocean was chosen because it offers a large amount of data describing low, mixed-phase clouds and will be used to calculate T5050 for the remainder of this paper. It should be noted that while we might expect the Northern Hemisphere clouds to be more glaciated than the Southern Hemisphere clouds due to a higher loading of continental dust [Atkinson et al., 2013; Kanitz et al., 2011; Tan et al., 2014], the T5050 from GCMs does not appear to change drastically between the Northern and Southern Hemisphere oceans (Figure 1b). A few models do appear to have a Northern Hemisphere T5050 that is a few kelvin higher than the Southern Hemisphere, but the majority have the same T5050 in both hemispheres (Table 1). The same T5050 in the Northern and Southern Hemispheres contradicts observations from surface lidar and CALIPSO [Hu et al., 2010; Kanitz et al., 2011; Tan et al., 2014].
The probability of observing either ice or liquid clouds as a function of temperature derived from aircraft data and surface-based lidar is shown for comparison to the model diagnosed T5050s [Bower et al., 1996; Cober et al., 2001; Isaac and Schemenauer, 1979; Kanitz et al., 2011; Korolev et al., 2003; Moss and Johnson, 1994; Mossop et al., 1970]. Data from Korolev et al. [2003] were revised as discussed in Storelvmo et al. [2015] to account for large ice particles shattering upon entering the inlets of cloud particle probes. Similar artifacts are likely to exist in the other aircraft data sets we present, and the aircraft data presented in Figure 1 is intended to show the range of observational estimates of mixed-phase behavior that exist in the literature. Both the revised and original aircraft data are shown. The aircraft data are measured in a variety of geographic regions and cloud regimes and span a temperature range that is almost as large as the models (Figure 1a). Surface-based lidar data from Kanitz et al. [2011] describing the probability of observing ice cloud is shown for a variety of polluted and pristine aerosol regimes. Naud et al. [2006] used data from the MODIS instrument to measure the fraction of ice clouds to all cloud detections in mid-latitude storms in the wintertime Pacific and Atlantic. Hu et al. [2010] used a global data set from the Cloud-Aerosol Lidar and Infrared Pathfinder Satellite Observation (CALIPSO) satellite to describe the probability of detecting liquid cloud near cloud top.

It should be noted that the T5050 parameter described in McCoy et al. [2015c] is based on GCM liquid and ice mass output, while the phase ratio described in Hu et al. [2010] is measured by the cloud lidar near cloud top. As discussed in Cesana et al. [2015], these are not directly comparable, except when ice is 90% of the mass and the simulated CALIPSO phase fraction and GCM mass phase fraction are relatively similar.
To estimate the mass phase ratio implied by CALIPSO measurements we fit T5050 to T1090 (10% liquid and 90% ice). This fit is used to predict $T^{5050}_{CALIPSO}$ as between 254K and 258K at 95% confidence (Figure 1a and Figure 2). While imperfect, the fit of the GCM T1090 to T5050 at least gives a crude estimate of how the CALIPSO derived T5050 might map to the mass ratio derived T5050. Similarly, we might expect the phase ratios measured by aircraft, surface-based lidar, and passive remote sensing from MODIS to not directly compare to the GCM mass phase ratio.

For the remainder of this study we will compare the GCM diagnosed T5050 to the CALIPSO inferred T5050. The derivation of CALIPSO T5050 is imperfect, but it is the only data set that has not been subset to a specific cloud type or geographic region. We present the historical in-situ estimates of T5050 in Figure 1a to offer insight into some of the potential origins of the spread in GCM parameterizations. T5050s diagnosed from Kanitz et al. [2011] and Naud et al. [2006] incorporate larger volumes of data and are less restricted by cloud type or geographic region. The results from these studies seem to cluster around the global estimate inferred by the CALIPSO instrument [Hu et al., 2010]. Evidently the range in T5050 inferred from these studies assuming that phase-ratio is predictive of mass-ratio is still uncertain (243K in pristine clouds near Punta Arenas, Chile to 260K in continental measurements from Leipzig, Germany). Even though the observed range of mixed-phase behaviors is wide, 18 out of 26 of the T5050s did not fall in the range indicated by these measurements. Six had T5050s that were lower than the most pristine lidar measurements (243K). The remaining twelve models had T5050s that were higher than the T5050 measured over the continental European site (260K).
In addition to the T5050, we use the liquid water path (LWP), total cloud fraction (CF), upwelling SW, skin temperature, and pressure velocity at 500hPa. These are retrieved for the period 1850-1900 in the historical emissions scenario for each of the GCMs. GCM data from the RCP8.5 emissions scenario from the period 2025-2075 are used to compare the climate mean-state to a warmed climate. In-cloud LWP is estimated as the LWP divided by CF. This estimate is very crude and is only intended to help disentangle the covariance between LWP and CF, rather than serve as a rigorous estimate of the in-cloud LWP. Monthly climatologies are created on a 2.5°x2.5° latitude-longitude grid for each model. The SW cloud feedback for each model is calculated as the temperature-mediated response of cloud-induced shortwave radiation anomalies in abrupt 4xCO2 simulations using the approximate partial radiative perturbation (APRP) method of Taylor et al. [2007].

In this study we focus on the effect of the mixed-phase parameterization on SW cloud reflectivity. Several clear a-priori reasons suggest that mixed-phase partitioning should affect the reflected SW, and there is a large spread in SW low-cloud feedbacks in the Southern Ocean [Zelinka et al., 2012; Zelinka et al., 2013]. The effect of the mixed-phase cloud parameterization on the reflected SW can occur through several pathways: ice particles tend to be larger and less reflective than liquid [Heymsfield et al., 2003; McCoy et al., 2014b]; ice tends to precipitate more easily than liquid and depletes the cloud water more rapidly [McCoy et al., 2015b; Morrison et al., 2011]; and ice precipitation can also thin clouds and decrease cloud fraction [Heymsfield et al., 2009; Morrison et al., 2011]. The effects of the mixed-phase parameterization on cloud
longwave (LW) radiative properties are less clear and there appears to be little LW cloud feedback in the Southern Ocean [Zelinka et al., 2012; Zelinka et al., 2013].

Inter-model differences in cloud parameterization are complex and it is difficult to isolate a particular factor as controlling inter-model behavior. To determine whether the diagnosed CMIP5 behaviors are consistent with adjustments to mixed-phase behavior and cloud cover in each GCM, we compare our analysis to an ensemble of CAM4 simulations where the cloud physics have been systematically perturbed.

The observations of cloud properties used in this study are provided by the Moderate Resolution Imaging Spectroradiometer (MODIS) instrument collection 5.1 dataset [Platnick et al., 2003]; and the unified microwave liquid water path data set described in O’Dell et al. [2008] (UWISC). Uncertainty in cloud cover was estimated by contrasting the cloud mask and the cloud fraction excluding partially cloudy pixels. The difference between these quantities is especially large in broken cloud [Marchand et al., 2010]. The range of the in-cloud LWP was estimated using the MODIS retrieval and the UWISC microwave LWP divided by the MODIS cloud mask.

3. Results

3.1 Effects on the climate mean-state

As shown over the Southern Ocean in McCoy et al. [2015c], T5050 is significantly negatively correlated with mean-state cloud liquid mass and significantly positively correlated with mean-state cloud ice mass. LWP strongly affects albedo, indicating that T5050 is likely to affect reflected SW. To examine the control of upwelling SW exerted by the model mixed-phase parameterization we regress T5050 on
annual mean upwelling SW across-models at each latitude and longitude (Figure 3).

Significant negative correlations occur over the high-latitude oceans and in regions of large-scale ascent near the equator. Low-topped, mixed-phase clouds are prevalent in high latitudes and convective clouds that contain substantial ice and liquid are prevalent in the convective tropics. The sign of the correlation with SW is consistent with the idea that models that more readily create ice contain less liquid and are therefore less reflective. Large, robust positive correlations between upwelling SW and T5050 exist across the subtropics indicating that models that do not maintain supercooled liquid at colder temperatures also reflect more SW. This is surprising because supercooled liquid clouds are uncommon in the subtropics. Even if supercooled liquid clouds were common in the subtropics, we would not expect this behavior based on the argument that models that create ice more readily have a lower LWP and therefore a lower albedo. The slope of the linear regression of upwelling SW on T5050 can be quite substantial in some regions. Sensitivities can reach 1 W/m² for a 1 degree change in T5050 (Figure 3), or 10 W/m² per standard deviation in T5050 across the GCMs considered in this study. To understand the relationship between T5050 and SW we will examine the behavior of various cloud properties across GCMs in relation to their mixed-phase parameterizations.

In nearly every location, models with higher T5050 have larger CF and smaller LWP and CF-normalized LWP (Figure 4). The relation between T5050 and these cloud properties is weaker in the tropics. The mean-state general circulation differs significantly between models, making the comparison of cloud properties in the convective tropics problematic. In order to compare differences in cloud properties between similar regimes we composite each cloud property on large-scale subsidence, in keeping with previous
studies [Bony et al., 2006]. We examine the correlation between cloud properties and T5050 as a function of large-scale vertical motion at 500 hPa. Equal quantiles of subsidence are created for the GCMs and the regression of GCM cloud properties on T5050 is performed in each quantile. LWP and the cloud-fraction-normalized LWP correlate negatively with T5050 across all vertical velocity bins (Figure 5). This correlation is significant at 95% confidence at pressure velocities less than 1.5 hPa/s. The cloud fraction is significantly correlated with T5050 across all pressure velocity regimes. The sign of this correlation is in contradiction to observations of supercooled liquid clouds, which show that enhanced glaciation (i.e., larger T5050) tends to decrease cloud fraction [Heymsfield et al., 2009; Morrison et al., 2011]. Additionally, interactions between ice and liquid do not appear to be a common feature of GCM cloud cover parameterizations [Qu et al., 2014], which makes it hard to provide a convincing physical explanation for why such a persistent correlation between CF and T5050 exists across the CMIP5 model suite. It seems more likely that an artificial compensation between cloud albedo and fraction exists in GCMs. Because liquid generally has a smaller particle size and is more reflective than ice [Heymsfield et al., 2003; McCoy et al., 2014b], models that maintain a large amount of supercooled liquid must have smaller mean-state low cloud cover such that the SW cloud radiative effect is in reasonable agreement with observations. This is consistent with previous studies that have noted that GCMs tend to create clouds that are too few and too bright compared to observations over the stratocumulus regimes [Bender et al., 2011; Engstrom et al., 2014; Gordon and Klein, 2014; Nam et al., 2012].
To examine the dependence of low cloud properties on mixed-phase parameterizations we consider the Southern Ocean. The Southern Ocean cloud cover in the control climate significantly affects the atmospheric general circulation in GCMs [Frierson and Hwang, 2012; Hwang and Frierson, 2013]. In addition, this region has extensive cloud cover [Haynes et al., 2011; McCoy et al., 2014b] and mixed-phase boundary layer cloud are prevalent [Huang et al., 2012], making it ideal for examining the interactions of in-cloud LWP, cloud cover, and phase parameterizations between models.

The annual mean cloud-fraction-normalized LWP in the Southern Ocean (40°S-70°S) is negatively correlated with T5050 across the GCMs (Figure 6a). Models with relatively low T5050 have clouds with a cloud-fraction-normalized LWP that is much higher than the observationally estimated range (Figure 6a). A positive correlation with CF (Figure 6c) and a negative correlation with LWP across models appear in the Southern Ocean (Figure 6b). Over 60% of the intermodel variance in cloud-fraction-normalized LWP (Figure 6a) is explained by the variance in T5050 between models. This is a particularly surprising result given the diversity in the model representation of cloud cover [Qu et al., 2014] and the relatively crude nature of the T5050 index used in this study.

Although the process level representation of mixed-phase cloud is complex [Ceppi et al., 2015; Klein et al., 2009; Komurcu, 2015; Komurcu et al., 2014; Morrison et al., 2011], we can utilize remote-sensing to offer a crude constraint on the in-cloud LWP and mixed-phase partitioning that is most in agreement with observations, indicating which models portray Southern Ocean low cloud less physically. The range of T5050
estimated from cloud lidar falls in the middle of the model diagnosed T5050s (Figure 1a and Figure 6). It is interesting to note that the historical range of mixed-phase partitioning inferred from regional aircraft observations of mixed-phase clouds roughly encompass the range of GCM behavior, while the surface-based lidar observations over a range of pristine and polluted regimes [Kanitz et al., 2011] are more closely clustered around the CALIPSO data (Figure 1a), which is averaged over the globe as a whole. Because the satellite lidar observations [Hu et al., 2010] represent a global estimate of T5050 they are used to compare to model spread in Figure 6. As noted in the methods section, the CALIPSO-inferred T5050 does not represent a perfect comparison, but it is consistent with the range of T5050s provided by surface-based lidar over a variety of aerosol regimes and allows at least a loose constraint on GCM behavior.

We may also estimate the in-cloud LWP from observations. We provide two estimates of this quantity: the in-cloud LWP measured by MODIS, which excludes cloud edges, and the microwave LWP from UWISC divided by the cloud mask from MODIS. Based on this estimate it appears that GCMs generally over-estimate the cloud-fraction-normalized LWP, despite generally not maintaining liquid to temperatures as low as those inferred from observations (Figure 1a). This overestimate of cloud-fraction-normalized LWP is consistent with previous investigations of cloud brightness and LWP [Bender et al., 2011; Engstrom et al., 2014; Jiang et al., 2012; Nam et al., 2012].

It is interesting that models do not appear to be able to represent the combination of cloud cover, LWP, and super-cooling that satellites observe in the current climate, even though their SW cloud radiative effect (CRE) is roughly consistent with CERES. Globally-averaged SWCRE over oceans from the models surveyed in this study was
between -54.7 Wm-2 and -40.5 Wm-2 with a median value of -49.8 Wm-2 and a standard deviation of 3 Wm-2. CERES EBAF TOA 2.8r estimates SWCRE over oceans as -47.15 Wm-2. While the maximum difference between models is nearly 15 Wm-2, the majority of the models are relatively close together.

It is unclear why the best-fit line of the models does not pass through the observationally estimated range of T5050 and LWP normalized by CF (Figure 6a). This may reflect an imperfect representation of the lidar analog of T5050, or it may indicate a systematic inability within GCMs to replicate the cloud microphysics that determine cloud albedo [Ekman, 2014; Nam et al., 2012]. If an imperfect representation of cloud microphysics is to blame, it is consistent with the rapidly evolving observational understanding of both cloud microphysics and aerosol sources. Passive remote sensing of cloud droplet number concentration is still highly uncertain [Cho et al., 2015; Grosvenor and Wood, 2014], and the sources of cloud condensation nuclei and ice nuclei in the pristine midlatitudes are still being determined [Burrows et al., 2013; McCoy et al., 2015d; Quinn and Bates, 2011; Wilson et al., 2015].

Compensation between LWP and CF across models is not exclusive to the Southern Ocean. The across-model correlations relating SW to CF and in-cloud LWP have opposite signs at almost all latitudes (Figure 7). Models with larger CF tend to have greater reflected SW radiation at the TOA. This is sensible because, all else being equal, over a dark ocean more clouds will yield a larger reflected SW. However, models with larger in-cloud LWP and LWP tend to have less outgoing SW across the subtropics and midlatitudes, indicating that LWP and CF differences are compensating each other.
Based on the correlation between T5050 and cloud fraction described above (Figure 5 and Figure 6c), it seems reasonable that critical relative humidity [Quaas, 2012], or other elements of the boundary layer cloud scheme in models that use more complex parameterizations [Bender, 2008; Mauritsen et al., 2012; Qu et al., 2014], are configured so that global-mean SWCRE is within only a few Wm$^{-2}$ of the observed value (see above). Cloud cover parameterizations are complex and it is difficult to compare diagnostically between models. To support the notion that the CMIP5 model behavior is originating from offsetting differences between the mixed-phase and cloud cover parameterizations we create a set of perturbed physics simulations in the Community Atmospheric Model Version 4 (CAM4).

We run CAM4 at 4°x5° horizontal resolution with fixed SST and a set of perturbed microphysics. CAM4 parameterizes mixed-phase physics and cloud cover in a highly idealized manner [Gent et al., 2011; Rasch and Kristjánsson, 1998]. Ice and liquid condensate are partitioned linearly as a function of temperature, and the cloud fraction is evaluated based on a critical relative humidity threshold. We alter the phase partitioning function and critical relative humidity for low cloud formation to create an ensemble of CAM4 simulations where the T5050 spans the range of T5050 in the CMIP5 models. The mixed-phase partitioning in this ensemble has been adjusted so that the T5050s of the different realizations of CAM4 span 230K-265K. In each case, lower T5050 results in a higher SWCRE as in-cloud LWP increases. The critical relative humidity for low cloud formation is then altered in each simulation so that the global SWCRE stays approximately constant. Each perturbed physics simulation in CAM4 is run for two years with the finite volume dynamical core. In CAM4 cloud microphysics are prescribed so
that the cloud droplet number concentration has fixed values over land, ocean, and ice. In our perturbed physics runs CAM4 is run with both the default marine cloud droplet number concentration ($N_d$) of 150 cm$^{-3}$ and with a marine $N_d$ of 50 cm$^{-3}$. The $N_d$ over land and ice were kept at their default values. Details of the CAM4 runs are given in Table 2.

When the T5050 from each ensemble member is correlated with outgoing SW, as in Figure 3, the correlation is negative across the midlatitudes and convective tropics and positive across the subtropics (Figure 8). This pattern is qualitatively similar to the pattern of correlation between SW and T5050 seen across members in the CMIP5 ensemble (Figure 3). The correlation across the CAM4 ensemble members is stronger than across the CMIP5 models, but this is quite reasonable. All the CAM4 ensemble members have the same cloud scheme with the exception of the critical RH, the marine $N_d$, and the mixed-phase partitioning. They also have approximately the same circulation because their SST is fixed. The CAM4 model is significantly more idealized than many of the newer CMIP5 models, but the similarity in the pattern is striking and supports the notion that mixed-phase cloud parameterizations are leading to significant local biases in mean SW flux.

The in-cloud LWP generated by the CAM4 simulations exhibits the same behavior as the 26 GCMs from CMIP5 (Figure 6a). The CAM4 LWP is negatively correlated with T5050 and the CAM4 CF is positively correlated with T5050. This is consistent with the behavior of the CMIP5 model ensemble. It is interesting to note that the CAM4 ensemble members’ CF appear to be less dependent on T5050 than the CMIP5 models, and the LWP is more strongly dependent on T5050. The sign of the trends is
reproduced and the positive correlation between T5050 and SW in the subtropics is quite strong. This demonstrates that the covariances across the CMIP5 model ensemble can be replicated in a single model by compensating enhancements in supercooled liquid and decreases in global cloud fraction.

3.2 Cloud Feedbacks

It is unclear how artificially compensating mixed-phase cloud and cloud fraction parameterizations would affect the climate system as a whole. This behavior is worrisome from the perspective of constraining the model representation of climate and climate change. The control climate TOA albedo over the Southern Ocean and the transition from subtropical stratocumulus to cumulus have been shown to significantly correlate with climate sensitivity and changes in atmospheric circulation in GCMs [Frierson and Hwang, 2012; Grise et al., 2015; Hwang and Frierson, 2013; Trenberth and Fasullo, 2009]. However, the compensating effects of CF and LWP make the Southern Ocean upwelling SW fairly independent of T5050, although strong correlations appear to exist at the edges of the Southern Ocean (Figure 3).

We will now discuss how model mixed-phase behavior appears to influence the cloud feedback. The GCM-predicted LWP increase with warming that drives the robust negative optical depth cloud feedback at high latitudes (Figure 9a) [Gordon and Klein, 2014; Kay et al., 2014; Zelinka et al., 2012; Zelinka et al., 2013] has been shown to exhibit a significant dependence on model T5050 [McCoy et al., 2015c]. Based on this mechanism we evaluate the dependence of SW cloud feedback on T5050. Models with higher T5050 tend to have more negative SW cloud feedback at higher latitudes and a
more positive feedback across the sub tropics (Figure 9b). We decompose the SW cloud
feedback into a contribution from changes in cloud albedo and a contribution from
changes in cloud amount.

The scattering component of the APRP SW cloud feedback, which is equivalent
to the albedo or optical depth cloud feedback (see Zelinka et al. [2012]), is negatively
correlated with T5050 at all latitudes. The scattering component of the cloud feedback
will hereafter be referred to as the cloud albedo feedback. The negative correlation
between cloud albedo feedback and T5050 is consistent with the idea that models that
have more ice in their mean state will be able to brighten more in a warming climate as
their ice transitions to liquid [McCoy et al., 2014a; McCoy et al., 2015c; Zelinka et al.,
2012, Tsushima et al., 2006]. To support this analysis we compare the cloud feedback,
which is calculated from the abrupt4xCO2 simulations, to the change in cloud properties
between the historical and RCP8.5 simulations. The change in estimated in-cloud LWP,
normalized by local change in surface temperature, is positively correlated with T5050 at
virtually all latitudes (Figure 9c). This is consistent with changes in cloud LWP driving
the increase in cloud albedo. For higher T5050s the latitude where ice transitions to liquid
is more equatorward. Since the insolation is stronger in these regions, the increase in
reflected SW from a given albedo increase is greater.

The amount component of the SW cloud feedback is correlated both positively
and negatively with T5050 (Figure 9b). A negative correlation between the SW cloud
amount feedback and T5050 is somewhat reasonable in regions of persistent mixed-phase
clouds such as the Southern Ocean. As GCMs transition to being more liquid dominated
the cloud fraction should increase due a decrease in efficient ice precipitation [Morrison
et al., 2011]. GCMs with a higher T5050 will have more ice to transition to liquid as the climate warms. The sign of the correlation in the Southern Hemisphere shifts from negative in the midlatitudes to positive in the subtropics. As the climate warms, models with a high T5050 tend to both decrease their subtropical cloud cover more strongly and enhance their Southern Ocean cloud cover more strongly (Figure 9c). Changes in cloud cover appear to be most strongly negatively correlated with T5050 in the stratocumulus regions (see Klein and Hartmann [1993]) (Figure 10). There does not seem to be a clear physical mechanism directly relating changes in subtropical low cloud changes to model mixed-phase parameterization. Because there is no physical mechanism explaining the linkage between subtropical liquid cloud and the mixed-phase parameterization, it seems likely that this behavior is a byproduct of adjustment in some global cloud-cover-controlling parameter in compensation for model mixed-phase parameterization. Singling out a parameter that has been adjusted is difficult. It is interesting to note that RH tends to decrease over subsidence regions and increase over ascent regions in global warming simulations (Figure 11). This behavior is similar across GCMs [Wright et al., 2010]. The pattern of drying and moistening is qualitatively consistent with the pattern of correlation between T5050 and changes in cloud fraction in GCMs (Figure 10). One potential explanation is that the GCMs adjust their critical RH in the same way that critical RH and T5050 were adjusted in our perturbed physics CAM4 ensemble (Table 2). If this is the case, high T5050 models would have low critical RH. A lower critical RH would make cloud cover more sensitive to variations in RH, all else being equal [Quaas, 2012; Sundqvist et al., 1989]. This would mean that high T5050 models would decrease cloud fraction more strongly in regions of drying and increase their cloud fraction more
strongly in regions of moistening. However, this is unlikely to be a unifying explanation across all of CMIP5. Many GCMs do not employ a simple critical RH threshold approach [Qu et al., 2014; Qu et al., 2015], and many other parameters may be adjusted to alter cloud cover globally and bring planetary albedo into a reasonable range [Bender, 2008; Mauritsen et al., 2012]. Moreover, low cloud cover is sensitive to several additional environmental factors with widely varying strengths across models [Qu et al., 2015], making it difficult to isolate the role of model-specific low cloud sensitivity to RH and model-specific changes in RH in driving the correlation between cloud amount feedback and T5050. Regardless of the adjustment method used, climate mean state cloud fraction is uniformly higher; subtropical cloud cover decreases more; and Southern Ocean cloud cover increases more in high T5050 GCMs. It appears that this behavior is linked to adjustment in some global cloud cover-controlling parameter to compensate for the choice of mixed-phase parameterization in a given GCM.

In summary, the SW cloud albedo feedback is negatively correlated with T5050, which is consistent with transitions from ice to liquid in a warming climate. The SW cloud amount feedback correlates positively and negatively with T5050, depending on region. We speculate that the larger decreases in subtropical low cloud cover in high T5050 GCMs may be due to across-model covariance between critical RH, or some other factor controlling the sensitivity of cloud cover to the large scale environment, and T5050.

It is interesting to note that the remote sensing-inferred range of T5050 [Cesana et al., 2015; Hu et al., 2010] shows that a substantial fraction of the CMIP5 models do not maintain liquid to sufficiently low temperatures (Figure 1a), indicating that the optical depth feedback is likely to be less negative than implied by the CMIP5 ensemble.
This is consistent with the conclusions of Gordon and Klein [2014]. Similarly, GCMs with a higher T5050 have a more positive subtropical cloud amount feedback, however the linkage between these model features appears to be artificial, in contrast to the linkage between the optical depth feedback and T5050. That is, if the linkage between cloud cover and T5050 was based on some sort of physical process we could hypothesize that excluding models with T5050s outside of the observational range would yield a reasonable range for the cloud amount feedback [Klein and Hall, 2015]. However, the linkage between T5050 and cloud amount feedback does not appear to be based on a physical mechanism. Thus, the most reasonable range of T5050 does not give us any insight into the most reasonable cloud amount feedback. In summary, our analysis of the midlatitude mixed-phase feedback, coupled with the growing body of evidence supporting a robustly positive cloud amount feedback in the subtropics [Bretherton and Blossey, 2014; Clement et al., 2009; Eastman et al., 2011; McCoy et al., 2015a; Myers and Norris, 2014; Qu et al., 2014; Qu et al., 2015], suggests that SW cloud amount feedback is positive globally.

4. Conclusions

We examine a wide selection of the GCMs from CMIP5 in relation to their cloud properties and mixed-phase behavior. GCMs effectively partition ice and liquid cloud condensate as a monotonic function of atmospheric temperature. This partitioning is highly variable between models (Figure 1a). The temperature where cloud ice and liquid are equally abundant (T5050) was used to typify the mixed-phase behavior in each model. The inter-model spread in T5050 was found to explain a significant amount of the
variance in cloud fraction and LWP across models (Figure 5). While the robust negative
correlation between T5050 and LWP is very sensible (if T5050 is high then liquid is not
maintained at low temperatures), the strong positive correlation between CF and T5050
does not have a clear physical explanation. If cloud fraction and mixed-phase properties
are coupled, observations indicate that the correlation between glaciation and cloud
fraction should be negative [Heymsfield et al., 2009; Morrison et al., 2011]. The
correlation between CF and T5050 is robustly positive across subsidence regimes and
geographic regions (Figure 4a and Figure 5). This behavior results in the T5050
correlating positively with upwelling SW across the subtropics and negatively across the
midlatitudes (Figure 3).

The Southern Ocean (40°S-70°S) is analyzed in the context of model mixed-phase
behavior and it is shown that models that do not maintain liquid at lower temperatures
tend to have more cloud cover, but less in-cloud liquid. It seems likely that the cloud
cover is being parameterized in such a way as to compensate for the mixed-phase
parameterization of each model, creating fewer clouds that contain too much liquid water.

A set of perturbed physics CAM4 simulations are performed where the T5050 is
set to values across a range like that shown by the CMIP5 model ensemble, and the
critical relative humidity for low cloud formation is adjusted so that the SWCRE is
consistent with observations from CERES. CAM4 replicates the dependence of cloud
fraction and liquid content on T5050 (Figure 6), suggesting that the critical relative
humidity may be artificially high to compensate for clouds that are too bright in models
with low T5050s (Figure 4). A diagram summarizing the hypothesized mechanisms
linking T5050 and climate mean-state cloud properties is shown in Figure 12a.
In addition to affecting the climate mean-state, mixed-phase parameterizations appear to affect SW cloud feedbacks. A diagram summarizing the mechanisms hypothesized to link T5050 to cloud feedbacks is provided in Figure 12b-c. The cloud amount component of the SW cloud feedback correlates both positively and negatively with T5050, depending on region. One might reasonably expect that, holding all other predictors of cloud cover constant, cloud amount in the persistently mixed-phase regions would increase as the climate warms due to mixed-phase clouds becoming liquid dominated (a negative feedback) [Heymsfield et al., 2009; Morrison et al., 2011]. This implies that models that glaciate more readily will have a larger increase in cloud fraction as easily precipitable ice is replaced with liquid in a warming climate. This is consistent with the Southern Ocean cloud amount feedback where mixed-phase clouds are prevalent (Figure 9). A stronger decrease in cloud fraction across the subtropics in models that glaciate more readily does not have a robust physical explanation, much less one that would be implemented across the CMIP5 models. It seems possible that across-model covariances between T5050 and cloud-coverage-controlling parameters among GCMs lead to a stronger decrease in subtropical cloud cover as the climate warms in high T5050 models.

The SW cloud albedo feedback correlates negatively with T5050 through the mid and high latitudes (Figure 9). This is sensible because GCMs with more ice in their control climates will be able to transition more ice to liquid. Because liquid is more reflective than ice this results in a negative optical depth feedback. While it is important to keep in mind that the observational mixed-phase partitionings shown in Figure 1a are not directly analogous to the GCM T5050, a significant number of GCMs (12/26)
considered in this study have a higher T5050 than inferred from either satellite observations or the most polluted continental ground-based lidar observations. This indicates that the cloud albedo feedback in the mid and high latitudes may be unrealistically negative in GCMs. This is consistent with the conclusions presented by Gordon and Klein [2014].

Overall, it is likely that the broad range in mixed-phase parameterizations and compensating changes in cloud fraction significantly affect the cloud properties in both the control and perturbed climates simulated by GCMs. It is evident that mixed-phase parameterizations must be more carefully vetted in the next generation of GCMs to reduce regional albedo biases and narrow the uncertainty in cloud feedback and climate sensitivity.
Acknowledgements

We acknowledge the World Climate Research Programme’s Working Group on Coupled Modelling, which is responsible for CMIP, and we thank the climate modeling centers for producing and making available their model output. For CMIP the U.S. Department of Energy’s Program for Climate Model Diagnosis and Intercomparison provides coordinating support and led development of software infrastructure in partnership with the Global Organization for Earth System Science Portals. CMIP5 model data may be downloaded from http://pcmdi9.llnl.gov. D.T. McCoy, D.L. Hartmann, and M.D. Zelinka were supported under DOE grant DE-SC0012580, and D.T. McCoy acknowledges government support awarded by DoD, Air Force Office of Scientific Research, National Defense Science and Engineering Graduate (NDSEG) Fellowship, 32 CFR 168a. The effort of M.D. Zelinka was performed under the auspices of the U.S. Department of Energy by Lawrence Livermore National Laboratory under contract DE-AC52-07NA27344. The authors wish to thank Xin Qu, B. Harrop and C. Wall for interesting discussions and advice.
Figure 1 Comparison of GCM and observed water partitioning behaviors. (a) Grey curves show the fraction of liquid as a function of temperature in the 26 GCMs examined in this study. Data describing liquid and ice partitioning is gathered over oceans between 30°S and 70°S. The temperature where ice and liquid are equally common (T5050) for each model is shown using a grey circle. Colored markers are used to denote previous observational estimates of T5050 derived from the probability of observing ice or liquid cloud as a function of temperature. If the T5050 is derived from an instrument that measures the probability of detecting liquid clouds a circle is used, if it measures the probability of detecting ice clouds a diamond is used. Data from Korolev et al. [2003], Cober et al. [2001], Mossop et al. [1970], Moss and Johnson [1994], Isaac and Schemenauer [1979], and Bower et al. [1996] are collected using aircraft in various cloud types and geographic regions. The ice probability from Korolev et al. [2003] is corrected for bouncing of ice particles [Storelvmo et al., 2015], and the original data is shown as a star. Surface-based lidar estimates from Kanitz...
et al. [2011] (K11) are shown for different aerosol regimes. Data collected by Naud et al. [2006] using the MODIS instrument described the fractional occurrence of ice clouds in midlatitude storms in the Atlantic and Pacific. It should be noted that the mass phase ratio from the GCMs and the probability of ice or liquid detection are not completely analogous quantities. Using the analysis of Cesana et al. [2015] the CALIPSO measurements [Hu et al., 2010] are used to infer the range of T5050 that would be diagnosed by a GCM using liquid and ice mass instead of ice and liquid detection probabilities (see text and Figure 2). This estimate is shown as a red line on the plot. The range of the aircraft and lidar measurements are noted using blue and green lines. (b) the T5050 calculated using GCM data taken from Northern Hemisphere oceans (30°N-70°N) are compared to the T5050 calculated using GCM data taken from the Southern Hemisphere oceans (30°S-70°S). The one-to-one line is shown using grey dashes.

Figure 2 The T5050 versus T1090 (90% ice) from GCMs. The observational value of T1090 from CALIPSO is used to predict the value of T5050 at 95% confidence (shown as black dashed lines).
Figure 3 The correlation and slope of the regression of T5050 on reflected SW across models. (Top) The correlation coefficient (r) between the annual mean upwelling SW and the T5050 that describes each of the 26 models. Correlations that are not significant at 95% confidence are shown with black dots. (Bottom) the slope of the across-model regression of the T5050 that describes each model and the annual-mean upwelling SW at each latitude and longitude. The units of the slope are W/m² of upwelling SW per degree K change in T5050.
Figure 4 as in Figure 3, but showing the correlation between T5050 and cloud properties across models. The correlation coefficient is shown relating T5050 to (a) CF, (b) LWP, and (c) LWP normalized by CF.

Figure 5 The correlation of T5050 with CF, LWP, and LWP/CF as a function of climatological, monthly pressure velocity at 500hPa. Correlations are taken using monthly climatologies from each model. Correlations that are significant at 95% confidence are shown using a solid line.
Figure 6 The correlation between annual mean values of LWP/CF, LWP, and CF averaged over the Southern Ocean between 40°S-70°S. Each model is shown as a black dot. The fit of each variable to T5050 is shown as a black line with 95% confidence on the fit shown in the hatched area. The $R^2$ of the fit is noted in the title. Results from the perturbed physics experiments in CAM4 are shown using purple crosses. The satellite-observed ranges for cloud properties and T5050 are shown as blue and purple shading.
Figure 7 The across-model correlation relating zonal-mean upwelling SW to LWP and CF. Correlations that are significant at 95% confidence are shown using a solid line.

Figure 8 As in Figure 3, but for the 17 ensemble members of CAM4 run with perturbed liquid and ice partitioning and fixed SST (see Table 2).
Figure 9 (a) shows the zonal, multi-model mean APRP SW cloud feedback and the contributions to the SW cloud feedback from changes in amount and scattering, which is analogous to optical depth. The zonal mean is only taken over oceans. (b) shows the correlation coefficient between each GCM’s T5050 and zonal-mean APRP SW cloud feedback. The correlation coefficients between T5050 and the amount and scattering contributions to the cloud feedback are also shown. (c) shows the correlation between T5050 and changes in cloud-fraction-normalized LWP and CF between the historical and RCP8.5 simulations normalized by changes in local surface temperature. If the correlation coefficient is significant at 95% confidence a solid line is used.
Figure 10 As in Figure 3, but showing the across-model correlation between T5050 and changes in CF. Changes in CF are normalized by the change in local surface temperature.
Figure 11 The multi-model mean change in RH at 850 hPa between the historical and RCP8.5 simulations. Changes in RH are normalized by the local change in surface temperature.
Figure 12. A flow chart describing the mechanisms discussed in this study that are hypothesized to link GCM mixed-phase parameterization (characterized as T5050) to the representation of (a) mean-state cloud properties, (b) the scattering feedback, and (c) the cloud amount feedback. The explanation is given in the context of an increase in T5050 in a hypothetical GCM. The effects on climate mean-state cloud properties and cloud feedbacks due to this perturbation in T5050 are described by the flow chart.
Table 1 List of models used in this study. The Northern and Southern Hemisphere T5050 are listed by each model. Models are sorted by Southern Hemisphere T5050. The difference of each model’s T5050 relative to the multi-model mean is noted as $\Delta$T5050 (MMM). The multi-model mean is calculated separately in each hemisphere. The upper and lower bounds of the estimated range of T5050 from CALIPSO are shown for comparison (Figure 2). Note that the Southern Ocean T5050 is used to infer the range of T5050 from CALIPSO.

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Table 2 Details of the CAM4 perturbed physics runs. The T5050, values that set the temperature ramp, critical RH, and SWCRE are listed for each run. The total condensate is decomposed into liquid and ice following a temperature ramp. The fraction of ice, $f_i$, is parameterized as $f_i = \frac{T - T_{\text{max}}}{T_{\text{min}} - T_{\text{max}}}$. The table is separated into runs that used the default value of marine Nd of 150 cm$^3$ or the perturbed value of 50 cm$^3$.

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References


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