Mixed-Phase Cloud Feedbacks

Daniel T. McCoy, Dennis L. Hartmann, Mark D. Zelinka

Abstract

This chapter introduces cloud feedbacks and describes salient features of their structure. One particularly pronounced feature simulated by global climate models (GCMs), is the contrast between the subtropics where cloud cover decreases with warming (a positive feedback) and the mid- and high-latitudes where cloud albedo increases with warming (a negative feedback). This increase in cloud albedo appears to be due to mixed-phase clouds (MPCs) transitioning from a more ice-dominated to more liquid-dominated state. The representation of this behavior in GCMs is discussed and is compared to satellite observations. Observational constraints on the mixed-phase cloud feedback show that the current generation of GCMs have too strong an increase in planetary albedo due to ice transitioning to liquid in the mid- and high-latitudes, indicating a potential underestimation of climate sensitivity. This behavior appears to be at least partially due to an inability to maintain supercooled liquid water at sufficiently low temperatures.

Keywords: Cloud feedback, global climate models, climate sensitivity, satellite observations, model tuning, Southern Ocean, emergent constraints

Introduction

Oceanic planetary boundary layer (PBL) cloud cover strongly affects reflected shortwave (SW) radiation, but has relatively little effect on the outgoing longwave (LW). This leads to a negative cloud radiative effect (CRE) that strongly affects the Earth's radiative balance [*Hartmann and Short*, 1980]. Because of this it is important to represent the response of PBL cloud to warming accurately to calculate 21st century climate change. Unfortunately, PBL clouds must be parameterized in GCMs. This is because turbulent motions with length scales smaller than a GCM grid cell create boundary-layer cloud. The ability of the PBL cloud parameterizations to reproduce cloud behavior in the current climate can be evaluated using observations, however it is difficult to use the existing observational record to evaluate the accuracy of the response of PBL cloud to warming. This results in a cloud feedback that is highly uncertain, even in the most recent generation of GCMs [*Bony et al.*, 2006; *Caldwell et al.*, 2013; *Vial et al.*, 2013; *Webb et al.*, 2013] and accounts for most of the uncertainty in the estimation of equilibrium climate sensitivity (ECS) [*Vial et al.*, 2013; *Webb et al.*, 2006].

Even though the global cloud feedback varies widely across GCMs the spatial structure of GCM cloud feedbacks are relatively similar [*Zelinka et al.*, 2012; *Zelinka et al.*, 2016; *Zelinka et al.*, 2013]. One particularly striking feature is the similarity in the latitudinal pattern of the response of cloud SW reflection to warming. We will refer to this change in the reflection of SW due to changes in cloud optical depth and amount with warming as the SW cloud feedback. The SW cloud feedback over oceans in the fifth climate model intercomparison project (CMIP5) is shown in Figure 1. Across GCMs the SW cloud feedback transitions from positive in the subtropics to negative poleward of around 50°. This is particularly pronounced in the Southern Hemisphere, but also occurs in the Northern Hemisphere. In GCMs this effect is not strongly coupled to shifts in midlatitude jet position [*Bender et al.*, 2011; *Ceppi and Hartmann*, 2015; *Ceppi et al.*, 2014; *Grise and Medeiros*, 2016]. The SW cloud feedback may be decomposed into contributions from cloud optical depth, amount, and altitude [*Zelinka et al.*, 2012]. The contributions from amount and optical depth, which dominate the SW, are shown in Figure 1. It is clear that the majority of the positive subtropical feedback originates from cloud area decreasing and revealing the relatively dark ocean beneath, while the negative midlatitude feedback is due to increasing cloud optical depth.

<< Insert Figure 1 here>>

Decreasing cloud cover with warming has been studied extensively and is a robust feature of both large eddy simulation and observational analysis [*Blossey et al.*, 2013; *Bretherton*, 2015; *Bretherton and Blossey*, 2014; *Bretherton et al.*, 2013; *Clement et al.*, 2009; *Klein et al.*, 1995; *Myers and Norris*, 2013; 2015; 2016; *Norris and Leovy*, 1994; *Norris et al.*, 2016; *Qu et al.*, 2014a; b; *Qu et al.*, 2015; *Rieck et al.*, 2012; *Seethala et al.*, 2015]. It is well known that increasing boundary layer stability increases cloud cover and that boundary layer stability increases as the planet warms [*Klein and Hartmann*, 1993; *Myers and Norris*, 2015; *Qu et al.*, 2014b; *Webb et al.*, 2013; *Wood and Bretherton*, 2006]. However, the increase in cloud cover due to increasing stability seems to be overwhelmed by decreases driven by thermodynamic mechanisms linked to sea surface temperature increases [*Bretherton and Blossey*, 2014]. This positive subtropical cloud amount feedback increases equilibrium climate sensitivity (ECS), , and the negative feedback at high latitudes has a counterbalancing effect on ECS. The robustness of the positive cloud amount feedback in the subtropics makes it particularly important to understand whether the negative feedback in the mid-latitudes is physical, and if so, if its strength is accurately represented.

The potential for a pronounced change in cloud optical depth due to mixed-phase clouds transitioning to a relatively more liquid-dominated state was first noted by *Mitchell et al.* [1989] and *Li and Le Treut* [1992]. Over the last decade this so-called mixed-phase cloud feedback has been of increasing interest in the climate modeling community [*Ceppi et al.*, 2016a; *Choi et al.*, 2014; *Kay et al.*, 2016; *McCoy et al.*, 2016; *Naud et al.*, 2006; *Tan and Storelvmo*, 2016; *Tan et al.*, 2016; *Tsushima et al.*, 2006] and has been recently featured in review articles [*Gettelman and Sherwood*, 2016; *Storelvmo et al.*, 2015]. It appears that representing mixed-phase cloud behavior in a way that is both physically robust and tractable from a modeling standpoint is becoming a widely acknowledged challenge in accurately predicting 21st century climate change.

As discussed in *Mitchell et al.* [1989] and *Li and Le Treut* [1992], the increase in cloud optical depth in the mid-latitudes appears to be due to transitions of mixed-phase cloud cover to a relatively less ice-dominated and more liquid-dominated state. At zero-th order this is simply because ice crystals tend to be larger than liquid droplets and thus less reflective for a constant amount of condensate [*McCoy et al.*, 2014; *Tsushima et al.*, 2006; *Zelinka et al.*, 2012]. In addition to this effect it is probable that the cloud water mass will increase with warming because ice precipitates much more efficiently than liquid [*Ceppi et al.*, 2016a; *Field and Heymsfield*, 2015; *Heymsfield et al.*, 2009; *McCoy et al.*, 2015a; *Mitchell et al.*, 1989; *H Morrison et al.*, 2011]. This *mixed-phase cloud feedback* is the subject of this chapter.

The mixed-phase cloud feedback is particularly difficult to constrain in GCMs for several reasons. These may be generally grouped into bottom-up and top-down uncertainties. From the bottom-up, the mixed-phase cloud feedback is uncertain because it is governed by ice nucleation; and other mixed-phase cloud physics, which are a complex interplay of different mechanisms, many of which still lack a strong constraint [*Atkinson et al.*, 2013; *Hoose and Möhler*, 2012; *H Morrison et al.*, 2011; *Murray et al.*, 2012; *Tan and Storelvmo*, 2016]. From the top down the feedback is uncertain because we cannot accurately measure the amount of cloud ice mass, making it difficult for models to be rigorously evaluated [*Carro-Calvo et al.*, 2016; *Hu et al.*, 2010; *Jiang et al.*, 2012]. Together, these top-down and bottom-up uncertainties yield a wide variety of mixed-phase behaviors in climate models and have led to mixed-phase cloud feedbacks being one of the major contributors to uncertainty in the cloud feedback, and thus climate sensitivity [*McCoy et al.*, 2016; *Zelinka et al.*, 2016]. In this chapter we will discuss the origins, mechanisms, and possible constraints on this feedback.

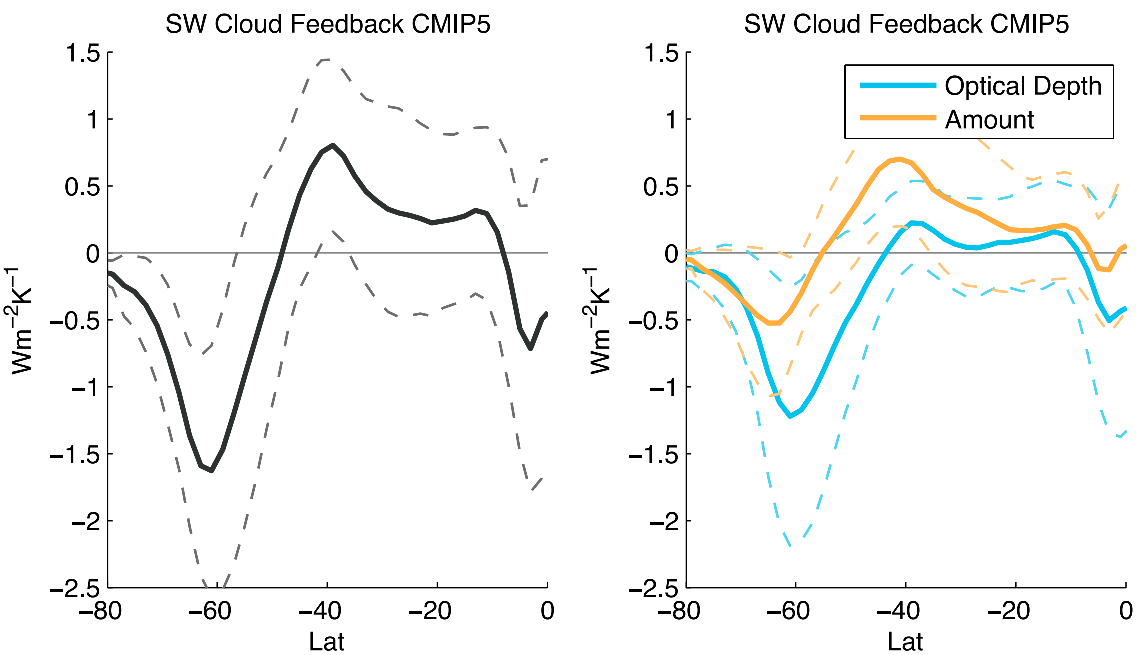

Figure 1 The SW cloud feedback of GCMs participating in CMIP5. The figure on the left shows the multi-model mean SW cloud feedback with one standard deviation across the GCMs shown as a dashed line. The same figure is shown on the right, but with SW cloud feedback decomposed into contributions from optical depth and amount feedbacks (see *Zelinka et al.* [2012]).

The Mixed-Phase Cloud Feedback in GCMs

As we discussed in the introduction, understanding the robustness and strength of the mixed-phase cloud feedback in GCMs is important for better constraining ECS and offering better predictions of 21st century climate change [*Tan et al.*, 2016]. Because mixed-phase cloud physics operate at a length scale smaller than global climate model resolution their behavior in GCMs must be parameterized. Readers interested in a more in-depth discussion of how MPCs are parameterized in GCMs should read chapter <<cite Kali Furtado's chapter on mixed-phase cloud parameterization>> of this text.

As noted above, parameterization of mixed-phase cloud physics is not the focus of this chapter, but it is useful to discuss it briefly. When confronted with the need to represent mixed-phase clouds, GCMs may either attempt to represent the nucleation of ice by aerosol and the growth of ice particles in MPCs, or may simply diagnose the partitioning of ice and liquid based on a function of temperature [*Cesana et al.*, 2015; *Tsushima et al.*, 2006]. Both approaches are problematic. Diagnosing liquid fraction as a function of atmospheric temperature is a very stable method of describing mixed-phase clouds, and can be implemented based on aircraft sampling of clouds (see *Bower et al.* [1996]), however it cannot represent the impacts of regional variability in ice nuclei (IN) on supercooled liquid clouds [*Atkinson et al.*, 2013; *Kanitz et al.*, 2011; *Murray et al.*, 2012]. Indeed, when observed over large regions, differences in cloud cover in regions that have access to IN (particularly dust) have noticeably less supercooled liquid [*Hu et al.*, 2010; *Kanitz et al.*, 2011; *Tan et al.*, 2014]. Sources of IN, particularly feldspar, are much more common in the Northern Hemisphere than in the Southern Hemisphere, leading to Northern Hemisphere clouds being more glaciated [*Atkinson et al.*, 2013; *A E Morrison et al.*, 2010; *Murray et al.*, 2012].

While mixed-phase cloud processes are complex, when a mixed-phase cloud is warmed it should transition from a more ice-dominated to a more liquid-dominated state as sinks of cloud water through ice-phase precipitation are suppressed [*Ceppi et al.*, 2016a; *McCoy et al.*, 2015a; *Mitchell et al.*, 1989; *H Morrison et al.*, 2011]. Because of the difference in the radiative properties of ice and liquid this results in an increase in upwelling SW and a negative optical depth feedback, providing that the size of ice crystals and liquid droplets are reasonably represented in a given GCM.

Do GCMs all agree on the mixed-phase cloud temperature range? By examining the behavior of mixed-phase clouds in GCMs as a function of atmospheric temperature it becomes clear that climate models disagree strongly as to the temperature range inhabited by mixed phase clouds. This is shown in Figure 2 for GCMs participating in CMIP5. To create the curves shown in Figure 2 for each GCM the fraction of liquid condensate is calculated within each model-level and latitude-longitude grid box. The fraction of liquid condensate is then averaged as a function of atmospheric temperature. This yields a gross statistical representation of the partitioning of ice and liquid as a function of temperature within each model. Examination of these curves reveals substantial disagreement between GCMs in terms of their mixed-phase condensate partitioning behavior. Some GCMs maintain liquid water to temperatures as low as 220K, well below the homogeneous freezing temperature, while some models are entirely composed of ice at temperatures as high as 260K. Overall, there is a nearly 35K range across models where ice and liquid are equally prevalent. While it is useful to discuss the temperature range for which mixed-phase clouds exist in a particular GCM, we will utilize the temperature at which ice and liquid are equally mixed for the remainder of this chapter. This is useful for brevity and characterizing the mixed-phase cloud temperature range of each model by a single number still has the capability to explain a significant amount of inter-model variability. We will refer to this quantity, the atmospheric temperature at which ice and liquid each make up 50% of existing condensate, as T5050 [*McCoy et al.*, 2016; *Naud et al.*, 2006].

<< Insert Figure 2 here >>

We have shown that in the models participating in CMIP5 there is an approximately 35K range in the temperature where ice and liquid are equally prevalent (Figure 2). Can the range of GCM ice to liquid partitioning shown in Figure 2 be constrained using observations? As noted above, the curves in Figure 2 show the temperature dependent partitioning of ice and liquid for vertical averages over GCM model levels (see *McCoy et al.* [2015a] for calculation details). Because of this it is hard to evaluate this model behavior with observations. Evidently this is not directly comparable to in-situ measurements made from an airplane, because airplane measurements are made in specific cloud regimes and at high temporal and spatial resolutions [*Bower et al.*, 1996; *Cober et al.*, 2001; *Isaac and Schemenauer*, 1979; *Korolev and Isaac*, 2003; *Moss and Johnson*, 1994; *Mossop et al.*, 1970; *Storelvmo et al.*, 2015].

A more direct comparison may be made between GCM phase partitioning and ground- and space-based remote sensing. *Naud et al.* [2006] utilized Moderate Resolution Imaging Spectroradiometer (MODIS) [*King et al.*, 2003] measurements of cloud top phase in northern hemisphere cyclones to show that cloud tops were equally partitioned between ice and liquid at roughly 255K in the Northern Hemisphere. Surface-based lidar estimates made by *Kanitz et al.* [2011] showed a T5050 that varied between 242K for pristine maritime regions and 260K for a continental site in Leipzig, Germany. This contrast between pristine maritime regions away from dust sources and continental sites is echoed by studies conducted using space-based lidar [*Hu et al.*, 2010; *Tan et al.*, 2014]. *Komurcu et al.* [2014] evaluated a selection of state of the art GCMs that do not treat ice and liquid partitioning as a function of temperature alone. The simulated cloud lidar output from these models showed that all six GCMs produced clouds that were much more glaciated than observed by the CALIPSO lidar [*Winker et al.*, 2009]. This result is reinforced by the analysis performed by *Cesana et al.* [2015] and *McCoy et al.* [2015a] who diagnosed the effective ice to liquid partitioning curve used by several of the models participating in CMIP5 (Figure 2). However, it was shown by *Cesana et al.* [2015] using simulated lidar output from GCMs that lidar-diagnosed ice to liquid partitioning is not directly comparable to the curves shown in Figure 2. This makes using space-borne observations to constrain ice in mixed-phase clouds in models problematic. *McCoy et al.* [2016] offered a rough estimate of the range where ice and liquid are equally mixed based on results from *Cesana et al.* [2015] and *Hu et al.* [2010]. This range was estimated at 254K-258K, in the global mean. This is a much smaller range than the range of temperatures from CMIP5 models (shown as a shaded area in Figure 2), and supports the idea that the current generation of GCMs tends to freeze liquid at temperatures that are too high [*Cesana et al.*, 2015; *Komurcu et al.*, 2014; *McCoy et al.*, 2016].

The most apparent effect of this diversity in model parameterization manifests itself in a wide variety of climatological cloud properties in GCMs. GCMs that maintain liquid down to colder temperatures tend to both have more liquid and less ice, as one would naïvely expect. This is shown in Figure 3 by examining how the T5050 temperature relates to the inter-model spread in historical LWP and IWP in CMIP5 GCMs. In addition, GCMs with a higher T5050 appear to have less overall cloud water (ice and liquid combined), which is generally consistent with the idea of enhanced precipitation efficiency in more glaciated clouds (see *H Morrison et al.* [2011], *Ceppi et al.* [2016a], and *McCoy et al.* [2015a]).

<<Insert Figure 3 here>>

Mixed-phase parameterizations have the capability to substantially influence the climate mean-state ice and liquid content in the mixed-phase regions. This variety in GCM climate mean-state ice and liquid water content may potentially be due to the weak observational constraint on ice-phase condensate in the current climate [*Jiang et al.*, 2012]. Only the MODIS and Cloudsat instruments offer estimates of the cloud ice water content through the vertical extent of the atmosphere. MODIS only retrieves IWP while the sun is up, which excludes nighttime and high-latitude winter. It is difficult to estimate an error in this retrieval beyond errors engendered by the assumed particle size distribution used in the retrieval and intercomparison of GCMs and observations by *Jiang et al.* [2012] assigned a factor of two uncertainty in the IWP retrieval from MODIS. The Cloudsat radar is highly sensitive to the partitioning of cloud ice and precipitation [*Eliasson et al.*, 2011] as well as to the assumed particle size distribution [*Jiang et al.*, 2012]. The uncertainty range in Cloudsat IWP assigned by *Jiang et al.* [2012] is between 50% and a factor of two depending whether or not columns that the cloud radar has identified as precipitating are excluded from the dataset. Ultimately, this wide variability in the IWP that can be consistent with observations means that GCMs are left with relatively little observational constraint in the creation of cloud parameterizations. Evidently GCM mixed-phase parameterizations play an important role in determining the column-integrated ice and liquid in mixed-phase regions. Does this matter to the SW cloud feedback? In general, it appears that models whose mixed-phase clouds contain a greater amount of ice that is susceptible to transitioning to water will have a larger increase in liquid water with warming. This is shown in Figure 4 by examining the change in LWP for a CO_2-induced warming, where the change in LWP has been normalized by surface temperature change.

Figure 4 shows that the intermodel spread in T5050 is strongly correlated with warming-induced increases in LWP. That is to say, models that glaciate their cloud cover more at warmer temperatures also increase their LWP more strongly in a warming climate and have a more pronounced negative optical depth feedback.

<<Insert Figure 4 here>>

The first intercomparison of GCM mixed-phase cloud feedbacks was performed by *Tsushima et al.* [2006], who analyzed five of the GCMs participating in the third climate model intercomparison project (CMIP3) and showed that there was a strong relationship between the phase partitioning in mixed-phase clouds and warming-induced increases in LWP. This dependence of the optical depth feedback on ice and liquid partitioning was also demonstrated by *Choi et al.* [2014], who created several versions of the CAM3 GCM with different ice and liquid partitioning functions. This behavior still appears to be a robust feature of CMIP5 models [*McCoy et al.*, 2015a]. *Ceppi et al.* [2016a] further demonstrated that this linkage is causal and not coincidental by perturbing the mixed-phase microphysical parameterizations in GFDL-AM2.1 and CESM-CAM5 showing that decreased efficiency of liquid water sinks through mixed-phase processes played a critical role in the increase in mid-latitude LWP with warming. It is interesting to note that there is not a consensus between GCMs participating in CMIP5 regarding whether the increase in LWP with warming is dominated by a simple repartitioning of condensate with warming, or if it is due to an increase in overall condensate mass in line with decreases in precipitation efficiency [*Ceppi et al.*, 2016a; *McCoy et al.*, 2015a]. In some GCMs the increase in LWP with warming may be explained entirely by replacing ice with liquid in line with increasing atmospheric temperature and the curves shown in Figure 2, while the increase in LWP in other GCMs is almost entirely due to increases in overall cloud condensate in line with suppression of frozen precipitation sinks as clouds move to a less glaciated state [*McCoy et al.*, 2015a]. Because of this model diversity, observations of changes in precipitation efficiency due to changes in prevalence of glaciated hydrometeors may be a useful constraint on the mixed-phase cloud feedback.

Viewing mixed-phase cloud properties in a zonal-mean sense is useful for discussing the large spread in cloud feedbacks in the Southern Ocean among GCMs. However, in order to provide more realistic model parameterization of mixed-phase cloud processes it is important to investigate how different cloud regimes contribute to the mixed-phase cloud feedback. Studies based on cyclone compositing in mid-latitude regions reveal that the change in LWP with warming and changes in reflected SW are not tightly coupled [*Bodas-Salcedo et al.*, 2016]. The clouds in cyclone composites that are responsible for the bulk of the radiative response to warming are non-frontal clouds, which are relatively thin and tend to be supercooled liquid, as opposed to the frontal clouds, which have significant amount of ice and liquid. Because the frontal clouds are already relatively opaque, increases in their optical depth are less important than increases in the optical depth of thin, non-frontal clouds [*Bodas-Salcedo et al.*, 2016].

Discussion of the mixed-phase cloud feedback tends to focus on mixed-, and ice-phase microphysics, but warm, liquid microphysics also have the potential to affect the mixed-phase cloud feedback. We have discussed the mixed-phase cloud feedback in the context of changes in LWP. However, cloud optical depth is controlled by both LWP and cloud droplet number concentration, which is in turn controlled by the availability of cloud condensation nuclei (CCN) [*Bréon et al.*, 2002; *Nakajima et al.*, 2001; *Sekiguchi et al.*, 2003; *Storelvmo et al.*, 2006; *Twomey*, 1977]. It is interesting to speculate on how changes in the availability of cloud condensation nuclei (CCN) with warming will affect the mixed-phase cloud feedback. As noted before, liquid droplets are much smaller than ice-crystals, and thus a given mass of cloud liquid is brighter than the same mass of ice. However, the availability of CCN, and thus the number concentration in the deglaciated cloud, also significantly affects the strength of the mixed-phase cloud feedback by affecting how relatively bright the newly minted liquid is [*McCoy et al.*, 2014]. The mixed-phase cloud feedback occurs in both the Northern and Southern midlatitudes. These are extremely different aerosol regimes. In the Northern Hemisphere anthropogenic CCN controls cloud microphysical properties [*Carslaw et al.*, 2013]. The Southern Ocean is highly pristine and accurate representation of its aerosol sources is difficult [*Hamilton et al.*, 2014]. Sources of CCN in the Southern Ocean are primarily natural and composed of sea spray and the sulfate from biogenic dimethyl sulfide (DMS) [*G. P. Ayers and Gras*, 1991; *Greg P. Ayers and Cainey*, 2007; *Charlson et al.*, 1987; *Kruger and Grassl*, 2011; *Lana et al.*, 2012; *McCoy et al.*, 2015b; *Meskhidze and Nenes*, 2006; 2010; *Vallina and Simó*, 2007; *Vallina et al.*, 2006]. Because a complex web of organisms produces DMS it is difficult to precisely diagnose how changes in the ocean biome will affect its production. It seems likely that biogenic emissions of DMS will decrease with increasing ocean acidification in a warming world [*Six et al.*, 2013], potentially blunting the negative mid-latitude mixed-phase cloud feedback. The control of Southern Ocean CCN by sea-spray aerosol is particularly interesting because sea spray emissions are closely tied to wind speed [*Grythe et al.*, 2014], and mixed-phase cloud parameterizations will affect wind speed through their control of the latitudinal gradient of absorbed SW radiation [*Ceppi et al.*, 2014; *McCoy et al.*, 2016], potentially yielding an interplay of these mechanisms.

Ultimately, the amount of liquid in a cloud plays a central role in determining its albedo. If the LWP in mixed-phase regions is so strongly controlled by the mixed-phase parameterization in a given GCM there must be another factor to counter-balance it and bring the planetary albedo into a reasonable agreement with observations. That is to say, the planetary albedo in a given GCM should be approximately consistent with observational estimates in the climate mean-state. If too little supercooled liquid is maintained in the clouds then this will lead to too low an albedo. Some other factor must increase the planetary albedo so that it is generally consistent with observations. It appears that, at least in the most recent generation of GCMs, this factor is the cloud fraction. It can be seen by regressing inter-model spread in cloud fraction on the mixed-phase characterization parameter, T5050, that models that glaciate clouds at warmer temperatures (higher T5050) both have lower LWP and a higher CF [*McCoy et al.*, 2016]. The correlation between T5050 and LWP is restricted to regions where a substantial amount of cloud exists above the melting level, but the inter-model correlation between T5050 and cloud area coverage appears to be a global phenomenon, which is clearly unphysical, especially since one would expect increased glaciation to decrease cloud cover [*Heymsfield et al.*, 2009; *McCoy et al.*, 2016]. One possible explanation of this behavior is that the critical relative humidity (RH) that GCMs use to parameterize cloud cover [*Bender*, 2008; *Mauritsen et al.*, 2012; *Quaas*, 2012] is adjusted to increase cloud cover and thus bring planetary albedo into a reasonable range. This is not an entirely unreasonable supposition and has been singled out as a common ‘tuning parameter’ [*Bender*, 2008; *Mauritsen et al.*, 2012]. Anecdotally, it may be seen that in studies which have directly addressed the sensitivity of Southern Ocean cloud properties to mixed-phase parameterizations that the critical RH has been adjusted to yield a control climate that is in energy balance [*Kay et al.*, 2016; *Tan et al.*, 2016]. Ultimately, this tuning between mixed-phase clouds and cloud fraction yields brighter subtropics and darker extratropics when model clouds glaciate at warmer temperatures [*McCoy et al.*, 2016]. It is interesting to note that this behavior is consistent with the emergent constraint on ECS offered by *Volodin* [2008] (see *Klein and Hall* [2015] for a discussion of emergent constraints).

In mixed-phase regions this tuning between cloud cover and liquid content in MPCs also results in clouds that are both too few, or cover too little area, and clouds that contain too much liquid and are too bright. In many GCMs this seesaw between cloud liquid and cloud area yields model cloud properties that agree poorly with observed cloud properties [*McCoy et al.*, 2016].

The choices made regarding mixed-phase cloud parameterizations in GCMs have far ranging impacts on model behavior. Can we use observations of mixed-phase cloud temperature range to provide a so-called emergent constraint [*Klein and Hall*, 2015] on climate sensitivity in the current generation of GCMs? The T5050 that characterizes mixed-phase cloud parameterization does not correlate strongly across models with equilibrium climate sensitivity [*McCoy et al.*, 2016]. This is because the subtropical cloud area feedback is more positive in models with a higher T5050, effectively counterbalancing the more negative cloud optical depth feedback in the midlatitudes (higher T5050 implies stronger increase in LWP with warming, see Figure 4). It is not clear why models with a higher T5050 have a more positive subtropical cloud amount feedback. One potential mechanism may be the positive feedbacks between boundary-layer radiative cooling, relative humidity, and cloud cover, as described by *Brient and Bony* [2013], thus linking climate mean-state cloud fraction to the response of cloud fraction to warming.

In summary, because of the wide variety of mixed-phase cloud behavior in the current GCMs cloud optical depth feedbacks are highly uncertain. However, GCMs must have a reasonable planetary albedo. Because of this necessity, uncertainty as to the amount of liquid in mixed-phase cloud cover results in a counterbalancing variability in cloud area. This seesaw between cloud area and mixed-phase cloud liquid results in cancellation between the negative optical depth feedback in the mid-latitudes and the positive cloud area feedback in the subtropics. Investigation by *Zelinka et al.* [2016] in CMIP3 and CMIP5 GCMs that provided ISCCP simulator output showed a 17% decrease in intermodel variance in net cloud feedback due to this anti-correlation between cloud amount and optical depth feedback. Given the robustness of the positive subtropical cloud area feedback (see introduction) it is probable that this compensation between cloud amount and optical depth feedbacks leads to an underestimation of climate sensitivity in the current generation of GCMs. In the next section we will discuss observational constraints on the mixed-phase cloud feedback.

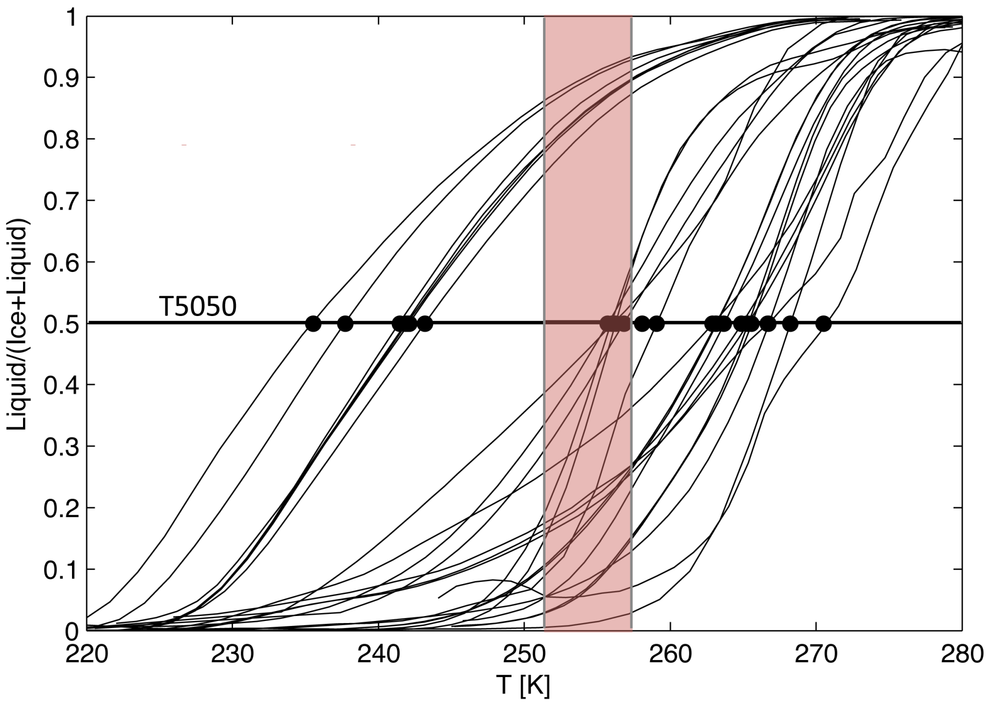

Figure 2 The fraction of cloud water that is liquid as a function of atmospheric temperature from a selection of GCMs participating in CMIP5 (for a full list of GCMs and details of the calculation see *McCoy et al.* [2015a]). The midpoint of the curves, where ice and liquid are equally mixed (T5050), is shown highlighted by dots. The range in of T5050 that would be inferred based on the CALIPSO cloud top phase [*Hu et al.*, 2010] combined with comparison between paritioning and simulated lidar data from *Cesana et al.* [2015]; [*Hu et al.*, 2010] is shown in red.

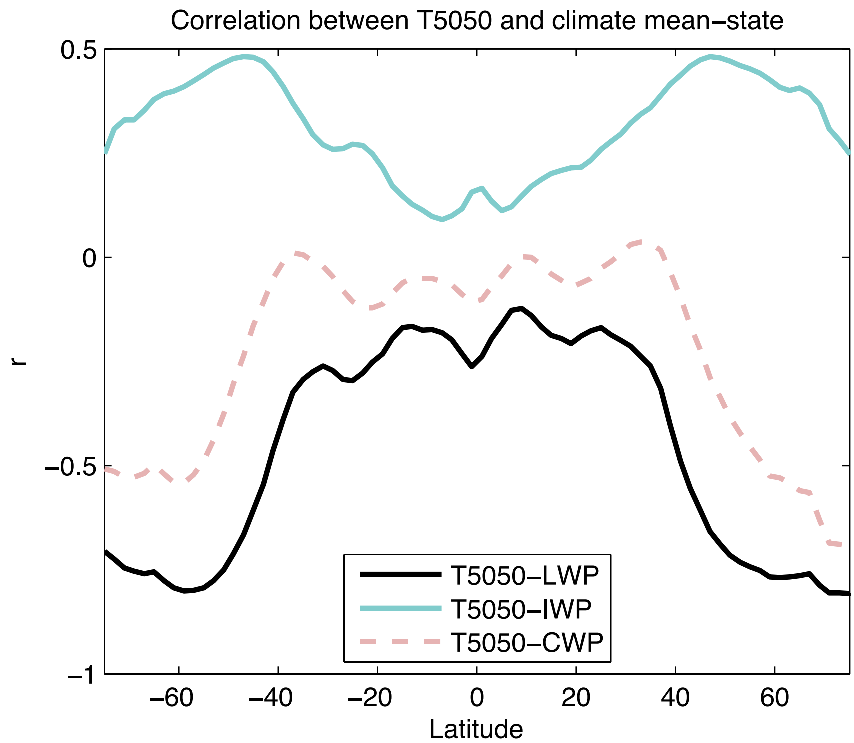

Figure 3 The across model correlation between T5050 (see Figure 2) and zonal-mean climate mean-state cloud properties over oceans: liquid water path (LWP), ice water path (IWP), and ice and liquid, or condensed water path (CWP). In the mid-latitudes, GCMs that freeze liquid at warmer temperatures (high T5050) have less liquid and more ice. They also have less overall ice and liquid water path. (Figure adapted from *McCoy et al.* [2016]).

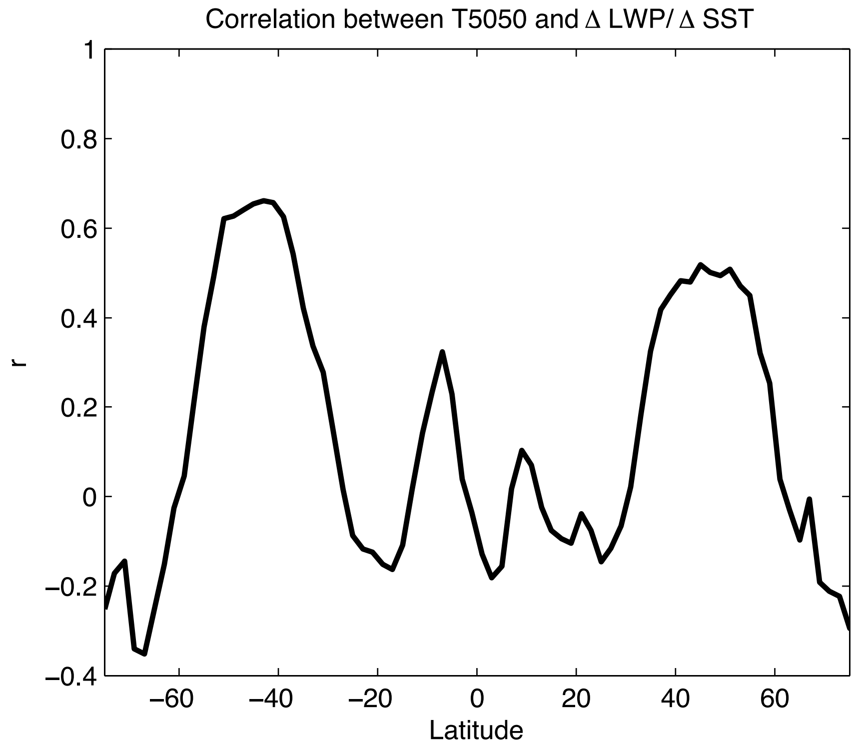

Figure 4 as in Figure 3, but showing the correlation between T5050 and change in zonal-mean LWP over oceans normalized by change in SST between historical and RCP8.5 scenarios in CMIP5. GCMs that have a mixed-phase scheme that has generated a large amount of susceptible ice in the climate mean state increase their liquid water path more with warming.

Observations of the mixed-phase cloud feedback

In the previous sections we have discussed the mixed-phase cloud feedback in the context of climate models. Can we observe the fingerprint of the mixed-phase cloud feedback in the observational record?

This task is somewhat hampered by the fact that the negative optical depth feedback should occur in the high- and mid-latitudes. Passive remote sensing is subject to substantial errors at low sun angles in the high-latitude wintertime [*Grosvenor and Wood*, 2014]. Further, the longer data records offered by ISCCP [*Rossow and Schiffer*, 1999] and PATMOS-x [*Heidinger et al.*, 2014] are not stable in a climate sense and must be corrected for artifacts [*Norris and Evan*, 2015].

Even with these observational uncertainties, can we see optical depth increasing with increasing surface temperature in the satellite record? Several studies have shown a pronounced increase in optical depth with warming over land at low temperatures [*Feigelson*, 1978; *Genio and Wolf*, 2000; *Tselioudis et al.*, 1992] while studies over ocean regions generally indicate no covariance between warming and optical depth, or a slight decrease [*Norris and Iacobellis*, 2005; *Tselioudis et al.*, 1992]. *Gordon and Klein* [2014] demonstrated that by comparing the optical depth feedback in GCMs with the optical depth-temperature relation detected by *Tselioudis et al.* [1992] that the strong negative cloud feedback diagnosed by GCMs was too negative.

Is there no evidence of a substantial increase in cloud optical depth with warming over oceans? The difficulty in robustly detecting an increase optical depth with increasing surface temperature in the observational record may reflect observational limitations, but it may also be partially due to the fact that many different mechanisms affect boundary-layer maritime cloud cover in a warming world. As noted earlier, cloud amount, and to some extent LWP, should generally decrease with enhanced surface temperature in the absence of mixed-phase transitions [*Bretherton and Blossey*, 2014], and it should increase due to increased boundary layer stability, which increases with surface temperature [*Klein and Hartmann*, 1993; *Myers and Norris*, 2015; *Qu et al.*, 2014a; b; *Qu et al.*, 2015; *Wood and Bretherton*, 2006]. Given the limited resolution of remote-sensing instruments, observational artifacts engendered by attempting to disentangle changes in cloud area from cloud optical depth may potentially make detecting the sensitivity of cloud albedo to temperature difficult.

Despite these issues, recent investigation directed at exploring the possibility of a negative cloud feedback due to mixed phase transitions have diagnosed a near-zero to weak increase in cloud optical depth with temperature. While these studies disagree somewhat as to the strength of the midlatitude SW cloud feedback, they agree that the most negative SW cloud feedbacks in GCMs are not consistent with the current observational record [*Ceppi et al.*, 2016b; *Terai et al.*, 2016].

The observationally constrained range of the Southern Ocean SW cloud feedback (including both amount and optical depth components) inferred by *Ceppi et al.* [2016b] is more negative than the range inferred by *Terai et al.* [2016], even though these studies share observational data sets. It is probable that this difference is due to systematic differences in the approaches taken by these studies to diagnosing the sensitivity of cloud optical depth to temperature. Different predictor variables may partially explain the different results arrived at by these studies. *Ceppi et al.* [2016b] regressed upon low- to mid-tropospheric temperature alone, while *Terai et al.* [2016] regressed upon both estimated inversion strength (EIS, [*Wood and Bretherton*, 2006]) and temperature. Strong and nonlinear covariation between EIS and tropospheric temperature [*Myers and Norris*, 2015] may lead to attributing variation in optical depth and cloud cover to tropospheric temperature that are due to variation in EIS if only temperature is used as a predictor. Another possible source of disagreement between these studies is that *Terai et al.* [2016] focused on the optical depth of low clouds, while *Ceppi et al.* [2016b] investigated changes in both cloud fraction and optical depth without restricting to low clouds. [*Ceppi et al.*, 2016b] diagnosed increases in both cloud cover and optical depth with warming leading to a negative overall SW cloud feedback. For these studies to be compared they must both be cast in terms of the SW cloud feedback as a whole. When *Terai et al.* [2016] replaced the optical depth portion of the SW cloud feedback in GCMs with the optical depth sensitivities that they diagnosed from observations their results were in agreement with the overall SW cloud feedback range inferred by *Ceppi et al.* [2016b]. This is summarized in Figure 5 for the Southern Ocean in the latitude band 45°S-60°S.

<< Insert Figure 5 here>

Ultimately, it appears that the observational record is in qualitative agreement that the most negative SW cloud feedbacks predicted by GCMs are too negative (Figure 5). This result is consistent with the results presented in the previous section: compared to observations, GCMs generally represent mixed-phase clouds as too glaciated at warm temperatures and increase LWP with warming too strongly. This too-strong dependence of LWP on temperature is corroborated by investigation of the long data record of microwave-observed LWP [*O'Dell et al.*, 2008] shown in *Ceppi et al.* [2016b]. The dependence of LWP on temperature derived in this study is shown in Figure 6. This provides a complimentary analysis to studies investigating the dependence of optical depth on temperature because optical depth is a function of both droplet number concentration and liquid water path. Showing that LWP is dependent on surface temperature disentangles possible trends in cloud microphysical properties.

<<Insert Figure 6 here>>

Constraint of Mixed-Phase properties in GCMs

Evidently the mixed-phase optical depth feedback is consistent with the observational record. As discussed above, the decisions that GCMs make concerning the handling of mixed-phase cloud cover strongly affects the negative optical depth feedback. Because of the pronounced hemispheric contrast in IN and, subsequently cloud glaciation[*Hu et al.*, 2010; *Kanitz et al.*, 2011; *Tan et al.*, 2014], GCMs should have a parameterization that responds to aerosol concentrations to properly represent mixed-phase cloud cover. One way to pursue this is to attempt to simply create the most advanced parameterization possible, but due to the complexity of mixed-phase cloud microphysics this has been exceedingly difficult to accomplish. Some processes that govern the mixed-phase system simply lack any strong observational constraint and they may be thought of as a so-called 'tunable-parameter' [*Tan and Storelvmo*, 2016].

Ultimately, the goal of adjusting the mixed-phase parameterization is to improve model biases in regional radiation budgets, and the global circulation [*Grise et al.*, 2015; *Kay et al.*, 2016; *Trenberth and Fasullo*, 2010]. One approach that has been used to address uncertainty in how to adjust the mixed-phase parameterization is to choose the parameters that govern mixed-phase clouds in GCMs in such a way that the simulated CALIPSO supercooled liquid occurrence in the GCM matches observations [*Tan and Storelvmo*, 2016]. In prognostic mixed-phase parameterizations there are many different factors that control the occurrence of supercooled liquid and there are many different combinations that may generate similar looking mixed-phase clouds. To explore this *Tan and Storelvmo* [2016] utilized a quasi-Monte Carlo sampling approach to investigate how different combinations of mixed-phase parameters satisfied observational constraints on supercooled liquid occurrence. In the sensitivity analysis conducted by *Tan and Storelvmo* [2016] it was found that the vast majority of supercooled liquid occurrence in the CAM5.1 GCM was governed by the Wegener-Bergeron-Findeisen (WBF) process [*Storelvmo and Tan*, 2015]. The importance of the WBF process inferred by *Tan and Storelvmo* [2016] is in agreement with the investigations of existing GCM parameterizations conducted by *Cesana et al.* [2015] and *Komurcu et al.* [2014], which also found that the WBF process exerted a significant control on the mixed-phase cloud behavior in an array of different GCMs. The version of CAM5.1 created by *Tan and Storelvmo* [2016] to agree best with CALIPSO was run with the fully-coupled version of the model in *Tan et al.* [2016] to investigate the response of the model to warming. It was found that this adjustment to bring the mixed-phase cloud parameterization into agreement with observed supercooled liquid occurrence raised the equilibrium climate sensitivity (ECS) substantially as it reduced the occurrence of glaciated cloud cover in the climate mean-state and reduced the negative mid-latitude optical depth cloud feedback.

The creation of a mixed-phase cloud scheme that is tuned to agree with our best space-borne measures of mixed-phase behavior in a state-of-the-art GCM substantially increases the ECS within that model. What does this mean for the range on ECS offered by model intercomparison? It should be noted that many other factors determine the ECS of a given GCM. However, the increase in CESM's ECS in *Tan et al.* [2016]'s analysis indicates that misrepresentation of mixed-phase clouds had led to an under-representation of ECS within that model. As noted earlier, in general, GCMs tend to glaciate mixed-phase clouds at temperatures that are too warm in the global-mean relative to space-borne estimates [*Cesana et al.*, 2015; *McCoy et al.*, 2016]. Tighter constraints on the mixed-phase parameterizations in these GCMs should lead to an increase in ECS in models with too little supercooled liquid as the magnitude of the mixed-phase cloud feedback is reduced.

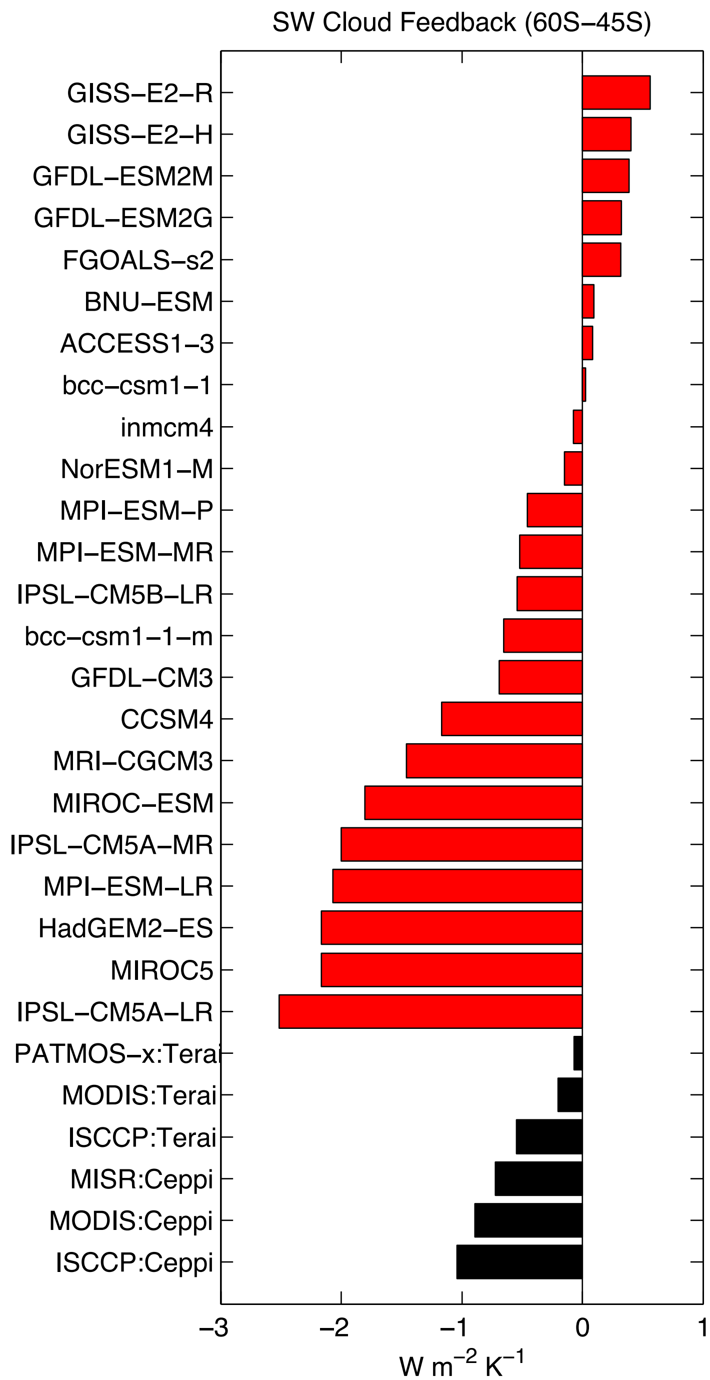

Figure 5 SW cloud feedback from GCMs participating in CMIP5 (see *Zelinka et al.* [2013]) (red) compared to observationally constrained estimates of the SW cloud feedback from *Ceppi et al.* [2016b] and *Terai et al.* [2016] (black). Averages are taken over the latitude band between 45°S and 60°S.

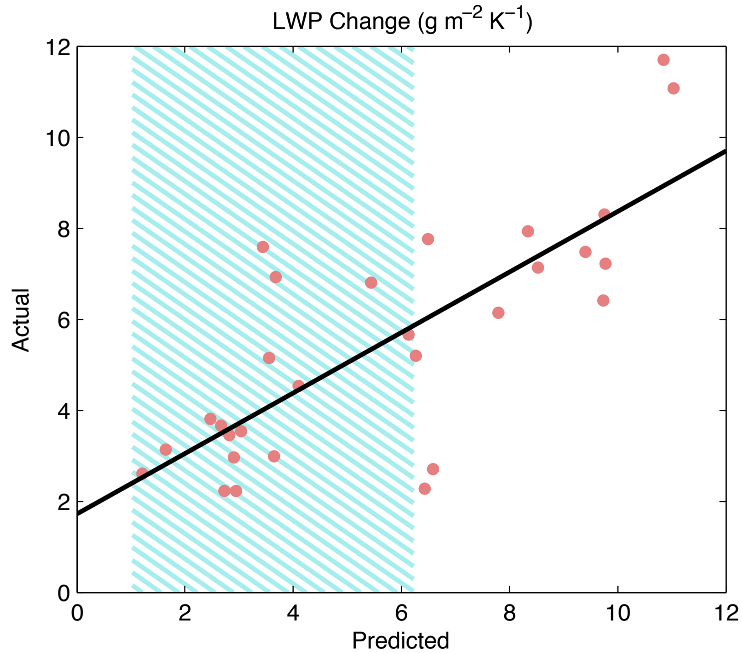

Figure 6 LWP change in GCMs predicted by their temperature sensitivity versus their response to warming. The observational range inferred from long-term microwave measurements of LWP is indicated using cross-hatching. (Adapted from *Ceppi et al.* [2016b]).

Summary

In this chapter we have discussed the negative cloud optical depth feedback that appears across GCMs in middle to high latitudes. This feedback is due to mixed-phase clouds transitioning to a less glaciated state as the planet warms. The uncertainty in the mixed-phase cloud feedback results from the wide variety of mixed-phase parameterizations that exist in the current generation of GCMs. Models that glaciate at warmer temperatures have a larger reservoir of ice in their mixed phase cloud cover that is susceptible to warming, which transitions to liquid as the climate warms and produce a stronger negative optical depth feedback. Cloud fraction is higher in models that glaciate clouds at warmer temperatures. This appears to be a result of the fact that a good fit to the observed cloud reflectivity is a product of cloud fraction and cloud optical depth. If models have more ice and thus a lower cloud optical depth, then they must have a higher cloud fraction to produce a realistic planetary albedo. This indirect control of cloud cover by the mixed-phase parameterizations in GCMs also produce an artifact of cancellation between subtropical positive cloud feedback and midlatitude negative cloud feedback. (Figure 1).

We discuss several recent papers that use the satellite observational record to evaluate the strength of the mixed-phase cloud feedback. These studies agree in diagnosing a cloud feedback in the mid-latitudes due to cloud optical depth changes that is either weakly negative or near zero. Overall, they agree in showing that many GCMs have SW cloud feedbacks that are too negative in the Southern Ocean (Figure 5)[*Ceppi et al.*, 2016b; *Terai et al.*, 2016]. We have also discussed studies that evaluate the mixed-phase temperature range in the current generation of GCMs. It was found that GCMs are generally unable to maintain supercooled liquid to low enough temperatures. Because of this GCMs generally over-represent the strength of the negative midlatitude cloud optical depth feedback [*McCoy et al.*, 2016]. This is also in agreement with evaluations made using a state of the art GCM that has had its mixed-phase parameterization constrained to better agree with space-borne observations of super-cooled liquid cloud occurrence [*Tan et al.*, 2016].

The representation of mixed-phase clouds in GCMs is important to the accurate prediction of 21st century climate change and to accurately represent the current climate. Overall, it is likely that this too-strong negative cloud optical depth feedback leads to an underestimation of climate sensitivity. Based on these different lines of investigation it seems clear that GCMs must carefully vet their mixed-phase parameterizations so that they agree, at least roughly, with observations of mixed-phase clouds.

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