Better Constraining Supercooled Clouds Could Reduce Projected Warming Spread

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Abstract. The increase of climate sensitivity to rising greenhouse gas concentrations in the coupled model intercomparison project phase 6 (CMIP6) Earth system models (ESMs) compared to CMIP5 ESMs is primarily attributed to a larger extratropical cloud response to climate change, referred to as cloud feedback. The ratio of supercooled liquid cloud water relative to all cloud water, termed liquid phase ratio (LPR), which has also notably increased in many recent ESMs, is thought to be a primary driver of the extratropical cloud feedback increase. Unlike the preponderance of previous studies that compare native model LPR directly with observations, here we evaluate LPR over three ESM generations against Cloud–Aerosol Lidar and Infrared Pathfinder Satellite Observations (CALIPSO) using an instrument simulator approach, which mimics instrument limitations and uses consistent cloud definitions and resolutions. We find that current coupled model intercomparison project (CMIP) ESMs collectively simulate greater LPR than previous CMIP generations and overestimate LPR compared to observations, contrary to previous findings, likely driven by past inconsistent comparisons of ESM outputs with CALIPSO observations. We further show that greater LPR in ESM present-day climate is unexpectedly correlated with a smaller extratropical cloud feedback, attributable to a decrease of cloud amountexceeding the increase of cloud optical depth. Finally, our results suggest that improving constraints on model LPR using our evaluation framework would likely reduce the spread in CMIP6 climate sensitivities, owing to its effect on extratropical cloud feedback from supercooled clouds.

INTRODUCTION

More liquid phase clouds are expected to prevail at the expense of ice clouds in response to climate warming. In general, liquid phase clouds are more reflective than ice clouds for a similar water content and they precipitate less efficiently, which is expected to increase cloud amount and optical depth[1], resulting in more solar radiation reflected back to space, weakening the initial warming through a negative cloud feedback (a relative cooling effect). These changes of cloud amount and optical depth in response to warming are commonly referred to as cloud amount and cloud optical depth feedbacks, respectively. The contribution of a phase shift to these cloud optical depth and amount feedbacks are maximum in the extratropics (defined as latitudes between 55˚ and 75˚ in both hemispheres), particularly over the Southern Ocean[2], where mixed-phase temperatures (0˚C < $T \lesssim$-40˚C) are omnipresent in the troposphere. More specifically, the strength of the optical depth feedback seems to depend on the amount of supercooled liquid present at mixed-phase temperatures, where both ice and liquid phases can coexist. Some studies have reported a link between increased liquid water mass relative to all condensed water (LPR_{mass}) in the current climate and reduced negative optical depth feedback in individual ESMs[3–5]. This possible link is particularly important since the weakening of the Coupled Model Intercomparison Project phase 6 (CMIP6) extratropical negative feedback relative to CMIP5 models has been shown to be the leading cause of larger spread and equilibrium climate sensitivity[2] (ECS) in CMIP6 models. Here we evaluate how well CMIP cloud phase is represented against satellite observations and then explore the links between changes in cloud phase and extratropical feedback across CMIP generations.

METHOD AND DATA

In this study, we characterize cloud phase transitions using the liquid phase ratio (LPR), defined as the ratio of the liquid cloud water content or frequency to the sum of the liquid and ice cloud water content or frequency, respectively LPR_{mass} and LPR_{freq}, ranging between 0 (ice clouds only) and 1 (liquid clouds only). We further use the temperature at which clouds are 50% liquid and 50% ice (i.e., LPR = 0.5), referred to as $T_{50/50}$ to estimate the ability of the model to produce supercooled water clouds. The smaller $T_{50/50}$ is in a model, the more supercooled clouds there will be relative to all clouds, and therefore, the larger its LPR. We use CALIPSO-GOCCP[6] (v2.9), which diagnoses cloud fraction and phase every 333 m along-track-resolution near-nadir lidar profiles for 480 m height intervals. To ensure a consistent evaluation of climate models, we use a simulator approach (Cesana and Chepfer, 2013; Chepfer et al., 2008) with nine CMIP6 models. Since the lidar simulator cloud phase module was not available in CMIP3 and CMIP5 models, we assume the effect of the CALIPSO simulator on CMIP6 LPR is similar in CMIP3 and CMIP5 models. Finally, we utilize cloud feedback computations from Zelinka et al.[1].

RESULTS

Cloud Phase Evaluation

Considerable attention is being paid to increasing LPR_{mass} in the CMIP6 generation[2,3,7–9] because CMIP3 and CMIP5 models have been reported to underestimate supercooled water clouds (too small LPR_{mass}) compared to satellite observations[10–12]. Here we examine cloud phase transition in CMIP models from a fixed set of modeling centers across three CMIP generations using a more consistent framework for model evaluation based on a simulator approach. Figure 1 shows how the evolution of cloud phase transition in three generations of CMIP models and how they compare against observations. $T_{50/50}$ – a metric often used to assess the fraction of supercooled clouds in an Earth System Model (ESM) – ranges from -1.6 to -32˚C based on the model raw output of liquid and ice water contents (without lidar simulator; Fig. 1a). Our results confirm that CMIP6 models simulate cooler $T_{50/50}$, and therefore greater LPR_{mass}, than their predecessors, with a similarly large spread. The diversity that emerges across CMIP generations is representative of the various methods used to partition liquid and ice phases in clouds from a simple temperature-based dependence[13] to more sophisticated microphysical schemes[14]. Based on previous literature, it is tempting to think that this increase of LPR_{mass} represents an improvement over the previous generations. However, when using a more consistent framework to evaluate the models, namely the simulator approach, we find the opposite conclusion: CMIP6 models collectively largely overestimate LPR_{freq} (Fig. 1b), with their mean $T_{50/50}$ being 7.2˚C less than in CALIPSO observations. Assuming that the effect of the lidar simulator found in the CMIP6 models is consistent across all CMIP generations (Methods), we derive a correspondingly smaller overestimate of LPR_{freq} in CMIP3 and CMIP5 models (Fig. 1b).

Most of the bias is driven by models with prescribed temperature-dependent phase partitioning while the models with more complex microphysics are in better agreement with the observations. CMIP6 models tend to simulate too many liquid-dominated clouds ($LPR_{freq} > 0.9$) between -25 and 0˚C, too few ice-dominated clouds ($LPR_{freq} < 0.1$) between -35 and -20˚C, and too many clouds in between ($0.1 <= LPR_{freq} <= 0.9$) at temperatures below -15˚C. Yet, the overestimate of liquid clouds (both pure and mixed phase) emerges as the main factor of the overall LPR_{freq} bias.

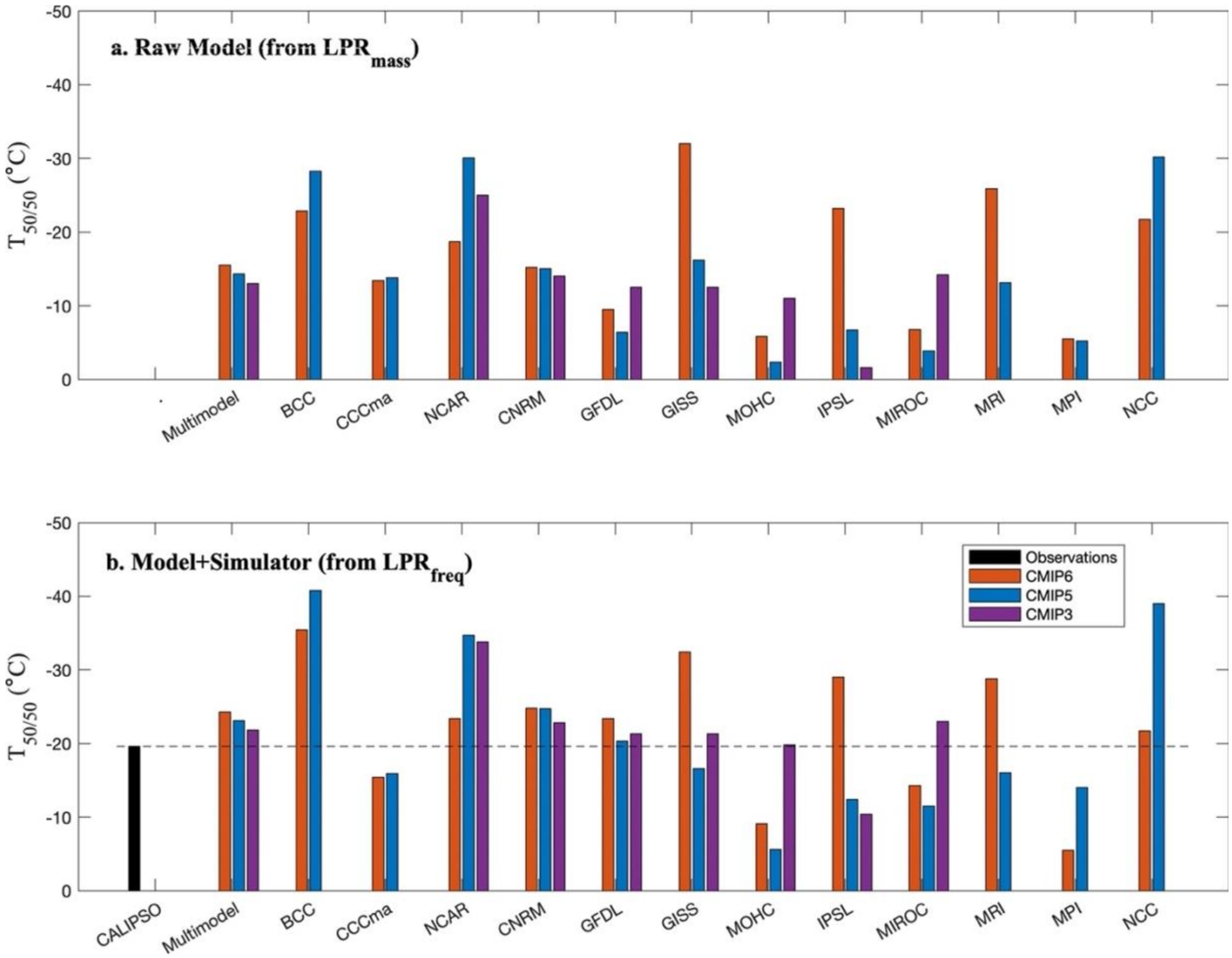

FIGURE 1: *Temperature at which liquid clouds transition to ice clouds for all different CMIP6, CMIP5 and CMIP3 models for (a) "raw" output (using water content LPR_{mass}) and for (b) model+simulator output (using cloud frequency, LPR_{freq}) and CALIPSO observations, expressed as the temperature at which clouds are 50% liquid and 50% ice (LPR = 0.5, noted $T_{50/50}$).*

Cloud Phase Effect on Cloud Feedback

Building on previous literature that suggests a link between cloud phase partitioning and extratropical cloud feedback in single-ESM studies[3–5], we study the relationship between $T_{50/50}$ and cloud feedback over the extratropics (55˚ to 75˚ latitude in both hemispheres). We further focus our analysis on the change in cloud feedback as a function of the change in $T_{50/50}$ between CMIP6 and CMIP5 climate models from each modeling center. On the one hand, we find that increasing LPR_{mass} in ESM (smaller $T_{50/50}$) is correlated with increased optical depth feedback (weaker negative or stronger positive), in agreement with previous single-ESM studies, because fewer ice clouds are "replaced" by liquid clouds in a warmer climate. On the other hand, our results indicate that greater LPR_{mass} also corresponds to a decrease of the cloud amount feedback (less positive or more negative) offsetting the optical depth feedback increase, a result that has not been reported before to our knowledge. We pinpoint this unexpected result to supercooled liquid clouds becoming less readily precipitating warm liquid clouds, as ice processes are suppressed.

Predicting the overall effect of a correction of CMIP6 $T_{50/50}$ bias using our observational constraint on models' climate sensitivities is challenging because it could also affect other feedbacks. However, based on our results, one could expect that an increase of $T_{50/50}$ –to match the observations– would generate an increase of the extratropical cloud feedback by strengthening the positive amount feedback more than the negative optical depth feedback. Finally, we expect that improving constraints on model LPR using our evaluation framework would reduce the spread in CMIP6 climate sensitivities by reducing and increasing the global feedback of high- and low-sensitivity models, respectively.

CONCLUSION

Although the representation of cloud phase has greatly improved[14,15], past inconsistent direct comparisons of ESM results with observations have likely encouraged modeling centers to increasing their liquid phase ratio too much in some CMIP6 models. A consequence of this increase is an unexpected underestimate of the multimodel mean $T_{50/50}$ from nine CMIP6 models by 7.2˚C compared to CALIPSO observations, which is 4.3˚C cooler (and therefore a worse match) than the earlier CMIP3 models. Additionally, our results shows that cloud phase partitioning changes systematically impact extratropical cloud feedback in CMIP models, which we mainly trace back to supercooled clouds becoming less readily precipitating warm liquid clouds in a future warmer climate. While predicting the overall effect of a correction of this bias in CMIP6 models remains difficult, our results suggest that using a more consistent observational constraints on model LPR would reduce the uncertainty in climate projections.

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