The Impact of Resolving Subkilometer Processes on Aerosol-Cloud Interactions of Low-Level Clouds in Global Model Simulations

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Abstract Subkilometer processes are critical to the physics of aerosol-cloud interaction (ACI) but have been dependent on parameterizations in global model simulations. We thus report the strength of ACI in the Ultra-Parameterized Community Atmosphere Model (UPCAM), a multiscale climate model that uses coarse exterior resolution to embed explicit cloud-resolving models with enough resolution (250 m horizontal, 20 m vertical) to quasi-resolve subkilometer eddies. To investigate the impact on ACIs, UPCAM’s simulations are compared to a coarser multiscale model with 4 km horizontal resolution. UPCAM produces cloud droplet number concentrations ($N_d$) and cloud liquid water path (LWP) values that are higher than the coarser model but equally plausible compared to observations. Our analysis focuses on the Northern Hemisphere (20–50°N) oceans, where historical aerosol increases have been largest. We find similarities in the overall radiative forcing from ACIs in the two models, but this belies fundamental underlying differences. The radiative forcing from increases in LWP is weaker in UPCAM, whereas the forcing from increases in $N_d$ is larger. Surprisingly, the weaker LWP increase is not due to a weaker increase in LWP in raining clouds, but a combination of weaker increase in LWP in nonraining clouds and a smaller fraction of raining clouds in UPCAM. The implication is that as global modeling moves toward finer than storm-resolving grids, nuanced model validation of ACI statistics conditioned on the existence of precipitation and good observational constraints on the baseline probability of precipitation will become key for tighter constraints and better conceptual understanding.

Plain Language Summary How aerosol particles impact the climate through their interactions with clouds is a significant source of uncertainty in quantifying the drivers of climate change over the past hundred years. Global climate models have so far been heavily reliant on approximations of the physical processes that occur at subkilometer scales, even though processes at those scales are important for representing the physics behind aerosol-cloud interactions. To address this gap, we develop and run a multiscale global model that embeds a finer-scale model (250 m in the horizontal and 20 m in the vertical) within the columns of a coarser-resolution global model. A pair of simulations with preindustrial and present-day aerosol emissions is used to quantify the impact of human aerosol emissions. They show that the climate impact of resolving subkilometer resolutions is relatively small. However, this masks some key differences. The increase in cloud water with increasing aerosols is substantially weaker when subkilometer motions are resolved. Most of this weakening is due to a weaker response in nonraining clouds and there being fewer clouds that rain in the high-resolution model. The simulation results point to observations of specific processes that can help further constrain the impact of aerosols on clouds and climate.

1. Introduction

The cloud radiative response to anthropogenic aerosol emissions, commonly called Effective Radiative Forcing from aerosol-cloud interaction (ERF$_{ac}$), is a key contributor to historical and future climate change and the largest uncertainty of all present-day anthropogenic-driven radiative forcings (IPCC, 2014)). Numerous cloud regimes and mechanisms contribute to this uncertainty. Process studies have shown various pathways by which aerosols can impact cloud radiative properties, especially those of low-level liquid cloud, which respond through direct perturbations to cloud droplet number (Twomey, 1977), through changes in cloud thickness, cloud cover, and cloud lifetime due to the suppression of precipitation (Albrecht, 1989;
Dagan et al., 2017; Pincus & Baker, 1994), and through entrainment feedbacks (Ackerman et al., 2004; Bretherton et al., 2007; Hill et al., 2009; Small et al., 2009; Xue & Feingold, 2006).

Representing many of the key aerosol-cloud interaction (ACI) mechanisms highlighted above requires accounting for effects of the cloud-forming eddies (Φ 100 m) in the planetary boundary layer. Therefore, one of the biggest challenges in studying ACI in global model simulations has been the range of scales that need to be considered to provide global estimates of aerosol radiative forcing. Present-day state-of-the-art global climate models (GCMs) have horizontal resolutions of order 100 km, and that has necessitated the reliance on parameterizations to represent subgrid variability and processes, such as convection and turbulence. Advances in supercomputing now mean that global storm-resolving models can be run on uniform meshes with horizontal spatial resolutions of 0.8–3 km (Sato et al., 2018; Stevens et al., 2019). However, it will still be decades until we arrive at global simulations that resolve subkilometer resolutions (Schneider et al., 2017) that are necessary to begin resolving planetary boundary layer eddies.

To fill this gap, global models built using a multiscale modeling framework (MMF) allow strategic undersampling of horizontal space to better resolve subgrid scales by replacing parameterizations of subgrid motion and variability with explicit cloud-resolving models (CRMs) embedded within GCM columns with typical spatial resolutions of >100 km (Grabowski, 2001; Khairoutdinov et al., 2005; Randall et al., 2003). In the past decade, despite their current limitations (e.g., idealized 2-D turbulence that is locally periodic), MMFs have proved important for understanding some important effects of explicit deep convection on planetary scales (Randall, 2013). Today, MMFs likewise allow an advance look at the role of boundary layer turbulence on global ACI. In the context of ACIs, past studies using MMF with 4 km grid resolution that resolve deep cumulus updrafts but not boundary layer eddies report that ACIs are weaker in these multiscale models than in conventionally parameterized GCMs (Kooperman et al., 2012; Wang, Ghan, Ovchinnikov, et al., 2011).

In this study, we employ the Ultra-Parameterized Community Atmosphere Model (UPCAM), a version of MMF that has a drastically increased resolution of the embedded CRM. This allows the world’s first GCM that also begins to resolve large boundary layer eddies. Early studies with UPCAM have shown that it has more realistic turbulence in cloud topped boundary layers than lower-resolution MMFs and has high enough resolution at the top of boundary layer clouds to begin resolving the cloud top entrainment processes (Parishani et al., 2017), which are important for key ACI processes like the sedimentation-entrainment feedback.

A secondary goal of the paper is to evolve best practices for diagnosing ACI physics underlying sensitivities in the era of increasingly explicit global simulations. Facilitating the comparison of global ACI simulations with high-resolution model simulations or with observations requires analyses beyond just examining the aggregated cloud radiative changes due to aerosol perturbations. On the one hand, analyses using process-oriented diagnostics highlight the importance of precipitation-forming microphysical processes in the models (Jing & Suzuki, 2018; Michibata et al., 2016; Mülmenstädt et al., 2020; Suzuki et al., 2013; Wang et al., 2012). Progress has also been made in finding meteorological regimes in which GCMs respond similarly to aerosol perturbations (e.g., S. Zhang et al., 2016), but we still struggle to identify which processes cause the response of GCMs to diverge in other meteorological regimes. Because models differ in their parameterizations and in the way subgrid-scale cloud processes are represented, the difficulty of identifying the drivers of ACI in GCMs and observations is as much a conceptual problem as a technical one. Recent analyses (Chen et al., 2014; Toll et al., 2017) point to the distinction of raining and nonraining clouds in helping us better conceptually understand how clouds respond to aerosol perturbations and where areas of agreement and disagreement between models and observations lie. This study builds on such a framework to distinguish between the raining cloud and nonraining cloud response in two separate models.

In section 2, we first describe the prognostic aerosol version of UPCAM and the unique simulation strategy used to run ACI simulations given the considerable computational costs of the model. Then we show that—despite lack of model tuning—UPCAM is competitive with previous models in capturing cloud properties relevant for ACI (section 3). We also demonstrate how a new analysis that utilizes the nudged-wind framework of previous studies allows us to test whether the mechanisms underlying our understanding of ACI are similarly simulated across different configurations of the same host model. And finally, we summarize our findings and highlight processes that need more observational constraints and further limited-area high-resolution simulations to hone in on key uncertainties in order to further constrain the strength of ACIs (section 4).
Table 1

| Model | Aerosol emission | GCM horizontal resolution | GCM/CRM vertical levels | CRM dx (m)/width (km) |
|-------|------------------|---------------------------|-------------------------|-----------------------|
| UPCAM | PI 4° × 5°       | 125                       | 250/8                   |
| PD    | 4° × 5°          | 125                       | 250/8                   |
| SPCAM | PI 4° × 5°       | 30                        | 4,000/128               |
| PD    | 4° × 5°          | 30                        | 4,000/128               |
| CAM5  | PI 4° × 5°       | N/A                       | N/A                     |
| PD    | 4° × 5°          | N/A                       | N/A                     |

2. Methods
2.1. UPCAM With Prognostic Aerosols

The goal of this study is to investigate the impact of resolving subkilometer eddies in a global simulation of ACIs. For our modeling simulations we have expanded the capabilities of the UPCAM beyond what was introduced in Parishani et al. (2017) and Parishani et al. (2018) to incorporate prognostic aerosols and double-moment microphysics in the cloud scheme.

UPCAM uses Version 5 of the Community Atmosphere Model (CAM5; Neale et al., 2012) as its host GCM with a finite-volume dynamical core. For its physical parameterizations, CAM5 uses the microphysics scheme of Morrison and Gettelman (2008), the shallow cumulus scheme of Park and Bretherton (2009), the turbulence scheme of Bretherton and Park (2009), the deep convection scheme of Zhang and McFarlane (1995), and the RRTMG radiation scheme (Iacono et al., 2008; Mlawer et al., 1997). The model uses the three-mode prognostic Modal Aerosol Model (MAM3; Liu et al., 2012). In UPCAM, as in the Super-Parameterized Community Atmosphere Model (SPCAM; Khairoutdinov et al., 2005) from which UPCAM was developed, a smaller CRM is embedded in each column of CAM5 to represent the cloud-scale motions and processes that are typically represented by cloud and turbulence parameterizations in typical GCMs. Following the convention of previous studies that used UPCAM and SPCAM, the embedded CRMs in SPCAM are two-dimensional, with one vertical and one horizontal dimension. UPCAM makes three notable changes to the SPCAM configurations that have previously been used to study ACI (Kooperman et al., 2012; Wang, Ghan, Easter, et al., 2011; K. Zhang et al., 2014). First, the horizontal grid spacing of the CRM grid has been shrunk from approximately 4 km down to 250 m. Second, the vertical resolution has been increased from 30 levels to 125 levels, with most of the resolution increases concentrated in the lowest 3 km of the model, where the atmospheric boundary layer resides. Third, to offset the computational costs incurred by increasing the resolution of the CRM, the domain extent of the embedded CRM has been shrunk from typical extents of 128–256 km down to 8 km. This means that deep convection is not as well resolved in the model nor are we able to simulate the impact of mesoscale organization on ACI. More details on UPCAM can be found in Parishani et al. (2017), and Table 1 provides a quick summary of the model configurations and boundary conditions used for our simulation.

To enable the study of ACIs, we have combined the existing UPCAM framework (Parishani et al., 2017) with the Explicit-Cloud Parameterized Pollutant (ECP) scheme, which uses statistics from the CRM to parameterize aerosol transport and wet scavenging (Gustafson et al., 2008; Wang, Ghan, Easter, et al., 2011). After reducing the internal time steps within ECP and the frequency with which we call ECP, we have produced a model that produces large eddies in the boundary layer and prognoses the impact of those cloud updrafts on the activation of interactive aerosols. We compare the ACI in UPCAM with SPCAM and CAM5.

2.2. Simulation Boundary Conditions

All simulations use year 2000 climatological sea surface temperature forcing, insolation, CO₂ concentration, and stratospheric ozone concentrations. The preindustrial simulation and the present-day simulation differ based on the aerosol and aerosol-precursor emissions, namely, anthropogenic SO₂, black carbon, and primary organic matter, created for the IPCC AR5 experiments and described by Liu et al. (2012) and Wang, Ghan, Ovchinnikov, et al. (2011). Sea salt and dust emissions remain a function of the environmental
conditions. The land model in all simulations is initialized by a 1 January land condition produced from a 25 year simulation with the baseline CAM5 model.

2.3. Computational Constraints and Simulation Strategy

Despite the limited horizontal extent of the embedded CRMs, the addition of the prognostic aerosols and double-moment microphysics increases the already high computational cost of these simulations. Even when run with a coarse $4^\circ \times 5^\circ$ (latitude × longitude) GCM, UPCAM completes 0.05 simulated years per day of computation when run on 828 cores.

To quantify ACI, we compare a simulation with present-day emissions and another simulation with the same boundary conditions, but with preindustrial aerosol emissions. Due to meteorological differences that will arise between these two simulations, retrieving the aerosol signal from the internal variability typically requires multiyear simulations (Kooperman et al., 2012; Wang, Ghan, Ovchinnikov, et al., 2011), which are beyond our computational constraints. Previous studies by Kooperman et al. (2012) and K. Zhang et al. (2014) have shown that the signal of the ACIs can be retrieved from much shorter simulations, on the order of 1 year, if the meteorological variability is controlled by nudging the wind fields in the models to a common meteorological field using Newtonian relaxation. In this study, only the horizontal winds of the model are nudged to those of year 2008 in the European Centre for Medium-range Weather Forecasting Interim Reanalysis product (Dee et al., 2011) following on the results of K. Zhang et al. (2014). They are nudged every GCM time step (5 min for UPCAM) to 6-hourly reanalysis fields with a relaxation timescale of also 6 hr.

Due to computational constraints, a continuous simulation covering the whole year would still take a better part of a year to complete. We, therefore, initialize 12 separate 6 week simulations starting at the beginning of each calendar month. We remove the first 2 weeks of simulation and use the remaining 4 weeks of simulation for analysis, as it takes roughly 2 weeks for the aerosol optical depth to reach roughly 80% of the global AOD values (liquid water paths [LWPs] equilibrate within a week). For consistency, we apply the same simulation strategy for both the CAM5 and SPCAM model simulations. Note that because aerosol emissions are prescribed, rather than concentrations, the background aerosol concentrations can differ across models. We also acknowledge that this simulation strategy may lead to slight underestimation of the aerosol concentrations in each simulation. We therefore choose a region of analysis that experiences the largest changes in aerosol concentrations.

2.4. Observations

For observational comparisons with the present-day simulations, we use two satellite-based cloud retrieval: the LWP retrieval of Elsaesser et al. (2017) and the cloud top droplet number concentration retrieval of Grosvenor et al. (2018). The LWP estimates are based on input from the Remote Sensing Systems (RSS) Version 7 0.25° resolution retrieval products (using retrievals of SSM/I, TMI, AMSR-E, WindSat, SSMIS, AMSR-2, and GMI satellites) and are gridded at 1° × 1° at the monthly timescale. The droplet number concentrations of Grosvenor et al. (2018) are daily 1° × 1° estimates based on optical depth and 3.7 µm effective radius data from the MODIS (MOderate Imaging Spectroradiometer) instrument aboard the Aqua satellite. It assumes that the clouds are adiabatic, droplet concentrations are constant through the depth of the cloud, and the ratio between the volume mean radius and the effective radius is constant.

We also make use of the low-cloud fractions (cloud fraction with tops below 3 km) as reported by the Multi-angle Imaging SpectroRadiometer (MISR) instrument aboard the Terra satellite. They are used to compare with low-cloud fractions retrieved in SPCAM and UPCAM given their ability to more accurately determine cloud top heights for clouds under strong inversions and for better capturing cloud fraction in broken cloud scenes (Marchand et al., 2010).

3. Results

3.1. Difference in Present-Day Cloud Properties Across Models

Because previous studies indicate the significance of low-level clouds in determining the strength of ACI in models (Wang et al., 2012; S. Zhang et al., 2016) and radiative properties are more easily derived for liquid clouds (e.g., section 3.3), subsequent analysis focuses on low-level cloud response and properties. The droplet number concentration ($N_d$) at cloud top is a key indicator of ACI, and estimates of cloud top $N_d$ have been retrieved from satellite observations (e.g., Bennartz, 2007; Grosvenor et al., 2018). Limiting our
analysis to low-level clouds (top < 4 km) and grid box cloud fractions greater than 20% for a more consistent comparison with observations, we find higher concentrations of cloud droplets in UPCAM compared to SPCAM (Figure 1). Whereas UPCAM mitigates SPCAM’s bias of having lower \( N_d \) than satellite retrievals over much of the open ocean, particularly over the Southern Pacific Ocean, it tends to overestimate \( N_d \) over anthropogenic sources and over the Atlantic Ocean. SPCAM shows a slightly better root-mean-square error (RMSE) with respect to satellite retrievals (219 cm\(^{-3}\)) compared to UPCAM (230 cm\(^{-3}\)). The similarity in skill is surprising, because UPCAM was not tuned to match observations. In terms of model differences, the higher \( N_d \) in UPCAM can be attributed to two aspects: a higher ratio of cloud condensation nuclei (CCN) activating into cloud droplets and a higher background CCN in the present-day (not shown). The latter is likely connected to the precipitation rate and frequency, which is a strong control of the wet scavenging of aerosols (Wood et al., 2012).

In addition to the activation of CCN into cloud droplets, the strength of the ACI also depends on the amount of baseline cloud water; for without clouds, there will be no ACI. If we plot the simulated cloud LWP in UPCAM and SPCAM alongside observational estimates (Elsaesser et al., 2017), we find that UPCAM shows better agreement with satellite microwave estimates, particularly in the subtropical/midlatitude regions (20–50\(^\circ\)), where UPCAM’s LWP bias of \(-25\) g m\(^{-2}\) is two thirds of SPCAM’s \(-38\) g m\(^{-2}\) bias. While the maps in Figure 1 are based on only 1 year of simulation, they indicate that—even without retuning the model physics parameters to achieve a more realistic climate in the simulation (e.g., Hourdin et al., 2017)—this meteorologically nudged configuration of UPCAM that includes two-moment microphysics produces a credible representation of clouds and aerosol-cloud processes, comparable to that in the well-documented SPCAM (Wang, Ghan, Ovchinnikov, et al., 2011; Wang et al., 2012). This gives us confidence to perform experiments simulating the cloud response to present-day anthropogenic emissions of aerosols. These UPCAM results represent an improvement from those in Parishani et al. (2017). We suspect that the use of interactive aerosols and two-moment microphysics have led to the improvement in cloud water through their tighter coupling of cloud-scale turbulence and convection with cloud microphysical processes, though nudging the meteorology might have also played a role (see Appendix A for more details).

Now that we have established that UPCAM produces clouds realistic enough to warrant study, especially in the midlatitudes, we investigate how the cloud properties differ between simulations with present-day and preindustrial aerosol emissions.

3.2. Quantifying the Impact of Anthropogenic Aerosols on Cloud Properties

Because the winds in all UPCAM and SPCAM simulations are nudged to the same ECMWF reanalysis winds, the cloud changes due to aerosol perturbations do not feed back onto the large-scale circulation. As a
Figure 2. The effective radiative forcing from aerosol-cloud interactions (ERFaci; a, d, and g), percent change in CCN concentration (b, e, and h), and percent change in cloud liquid water path (c, f, and i) in UPCAM (top row), SPCAM (middle row), and CAM5 (bottom row). Dotted lines indicate the 20°N and 50°N parallels.

result, the cloud responses in these simulations do not include any responses arising from aerosol-induced changes in the circulation, and we can study cloud responses to aerosol that—because they are independent of changes in large-scale meteorology—are as close to a pure aerosol-induced cloud response as can be achieved in a GCM. To quantify the impact of aerosols on cloud radiative properties, we use the approximate partial radiative perturbation (APRP) method employed by Zelinka et al. (2014) to calculate Effective Radiative Forcing from ACIs (ERFaci) between the present-day (PD) and preindustrial (PI) emission simulations across model configurations (Figure 2, left panels).

We begin with a cross check on our simulation design by comparing with past work that investigated the effect of classical superparameterization on ERFaci. For this comparison, we perform the same type of nudged hindcasts using Version 5.1 of the conventionally parameterized CAM5 to demonstrate whether the idealizations of our simulation strategy nonetheless produce consistent results with previous studies that were not as throughput limited. Figure 2 supports this expectation, showing differences between SPCAM and CAM5 that previous studies have noted with longer simulations (Kooperman et al., 2012; Wang, Ghan, Ovchinnikov, et al., 2011): a larger increase in aerosol concentrations between present-day and preindustrial simulations, a weaker relative increase in cloud LWP, and a subsequently weaker cloud radiative response (less negative) in SPCAM compared to CAM5. That we are able to reproduce previously reported results with a year of overlapped 6 week nudged simulations gives us confidence that this simulation strategy captures the key differences in ACIs seen across model configurations run for longer periods.

We now turn to our main interest—comparing UPCAM, as the first GCM to avoid parameterization of the boundary layer in such tests, with SPCAM and CAM5 simulations. We acknowledge that the ERFaci in UPCAM differs from the other models in other regions of the globe such as the southeast Pacific, but for the following three reasons, our focus is on the cloud response over the Northern Hemisphere (NH) oceans between 20°N and 50°N. First, ERFaci in this region is already known to be sensitive to how convection is parameterized (Wang, Ghan, Ovchinnikov, et al., 2011, and our Figures 2d and 2g). Second, this is where the largest increases in oceanic CCN occur relative to preindustrial emissions scenarios (Figure 2). Third, UPCAM’s baseline marine cloud properties are least biased in this region; that is, by excluding the Tropics,
Figure 3. The ERF_{aci} from scattering and absorption averaged over the Northern Hemisphere ocean (20–50°N) in UPCAM (blue), SPCAM (orange), and CAM5 (green). Vertical lines indicate the 95% confidence interval of the mean taken from daily variations over the 4 week averaging period. Despite agreeing on the time-mean, UPCAM and SPCAM have distinct seasonal cycles of ERF_{aci}.

we intentionally avoid most of the deep convective regions where we expect UPCAM to be less realistic (Parishani et al., 2017).

Qualitatively, compared to its precursor models, UPCAM leads to a weaker and more geographically diffuse ERF_{aci} over oceans between 20°N and 50°N. In SPCAM and CAM5, the strongest ERF_{aci} over the NH ocean occurs over the northern stretch of the North Pacific (Figures 2d and 2g), where the LWP increase is notably high in both models (Figures 2f and 2i) with comparably little Atlantic signal. In UPCAM, the ERF_{aci} in the Pacific region is weaker (Figure 2a), consistent with the much smaller increase in LWP in the area (Figure 2c). Unlike the other two models, UPCAM exhibits a weak ERF_{aci} over a broader area encompassing both the North Pacific and North Atlantic.

Quantitatively, while the overall time-mean NH midlatitude ERF_{aci} of UPCAM is remarkably similar in magnitude to that of SPCAM, fundamental differences in the underlying seasonality point to distinct physics when boundary layer eddies are quasi-resolved. When we take the spatial average of ERF_{aci} over the NH ocean (Figure 3), the annual mean shortwave ERF_{aci} in UPCAM (−2.0 W m^{-2}) is only slightly lower than in SPCAM (−2.3 W m^{-2}) (−4.0 W m^{-2} in CAM5). To see whether the ERF_{aci} differences are similar across seasons, we average the ERF_{aci} over the NH oceans in each month and plot the mean ERF_{aci} as a function of calendar month in Figure 3. A distinct summer peak in the shortwave response occurs in SPCAM and CAM5, which mainly follows the change in insolation over the NH. The UPCAM simulation, on the other hand, has its peak in ERF_{aci} in the months surrounding February. We investigate the reasons for the difference between the UPCAM and SPCAM simulations in the next section.

3.3. The ERF_{aci} Differences Between UPCAM and SPCAM Over the NH Oceans

Following the previous analysis, subsequent analyses in the next two subsections will be focused over the oceans between 20°N and 50°N. Almost all of the difference in shortwave ERF_{aci} is due to changes in the shortwave scattering and absorption of clouds, rather than changes in cloud cover (Figure 3). Both an increase in N_d and an increase in cloud LWP can contribute to a brightening of the cloud and a negative ERF_{aci}. To estimate their relative importance in explaining the model differences between SPCAM and UPCAM, we predict the change in SW radiation ΔR_{sw} as the sum of the contribution from relative N_d changes ΔN_d/N_d and relative LWP changes ΔL/L building on the relationship from (Ackerman et al., 2000) (see also Bellouin et al., 2020)

\[
\Delta R_{sw} = R_{sw,clear,PD} \alpha_{cl,d,PI}(1 - \alpha_{cl,d,PI}) f_{low,PI} \left( \frac{\Delta N_d}{3N_d,PI} + \frac{5\Delta L}{6L_{PI}} \right),
\]

where R_{sw,clear,PD} is the surface shortwave radiation in clear-sky conditions, \alpha_{cl,d,PI} is the preindustrial cloud albedo, and f_{low,PI} is the preindustrial low-cloud fraction. Other methods of decomposition exist (Gryspeerdt
et al., 2020; Mülmenstädt et al., 2019), and we readily admit that the prediction based on Equation 1 is imperfect, given that it assumes that the clouds are adiabatic, only accounts for radiative changes in low clouds, and tends to underestimate the actual change in ERFaci (Figure 4). Nonetheless, its physical underpinnings and the fact that it explains up to 80% of the actual ERFaci, including the seasonality differences between SPCAM and UPCAM, justifies its use in understanding them.

The solid vertical bars in Figure 4 are the Equation 1-predicted shortwave cloud radiative response from changes in LWP, whereas the hatched bars are those predicted from changes in Nd. Figure 4 first shows that the stronger summertime (June–August, JJA) shortwave ERFaci in SPCAM, compared to UPCAM, can be mostly traced to a much weaker LWP response in UPCAM (Figure 4). The ERFaci difference between SPCAM and UPCAM is largest in the summer months when the North Pacific regions of large LWP changes in SPCAM are illuminated. The relative change of LWP in SPCAM varies little with the month of the season, but because most of the LWP response is confined to the North Pacific (Figure 2d), its radiative impact is strongest during the boreal summer.

On the other hand, most of the stronger ERFaci in UPCAM during the winter and fall months come from the contributions related to Nd changes. One might first suspect that this is due to a difference in the activation of cloud droplets, but actually, this difference is mainly due to UPCAM having more low clouds (Figure 5). Because UPCAM simulates more low clouds during the winter months, particularly over the better illuminated low latitudes, the radiative impact of cloud brightening from increased cloud droplets is larger in UPCAM than in SPCAM. Given the large discrepancy of low-clouds in SPCAM and UPCAM in the winter months, one may wonder which is more consistent with observations. A direct comparison with observations is difficult, because what is shown in Figure 5 is the low-cloud fraction of clouds for which Nd were calculated (see section 3.1 for details). Similar retrievals from observations do not exist. Despite their biases, the closest comparison may be with the low-cloud fractions from the MISR instrument, which show more consistency with the UPCAM estimates. The differences in cloud cover in Figure 5 however do not explain why SPCAM has a larger LWP contribution than UPCAM in Figure 4. In the following section, we dig deeper into why the LWP response is stronger in SPCAM.

3.4. The Mechanisms Behind the Nd and LWP Response in UPCAM and SPCAM
To better understand the conditions that lead to a larger increase in LWP in SPCAM than in UPCAM, we can match cloud conditions at a particular time and location from the present-day simulation with those from the
Figure 5. The predicted SW change over the NH ocean due to relative Nd changes in UPCAM (blue) and SPCAM (orange) are shown as hatched bars. Blue dotted lines indicate the insolation-weighted fraction of clouds for which Nd are calculated in the present-day simulations of UP (see right y axis for scale), while orange dotted lines indicate the same for simulations of SP. Gray dotted lines are low-cloud fraction (below 3 km) from MISR, also weighted by solar insolation.

same time and location in the preindustrial simulation. Because the winds in preindustrial and present-day simulations are nudged to the same ECMWF reanalysis winds, we can assume that the large-scale conditions are largely identical between the simulations. This allows us to ask whether a cloud that is raining in the preindustrial simulation will respond differently to increases in aerosols compared to a cloud that is not raining (with other meteorological factors kept constant).

By distinguishing the responses of raining clouds from nonraining ones, the causes for a stronger or weaker cloud lifetime effect can be disentangled. The cloud lifetime effect, as originally described by Albrecht (1989), proposes that aerosol-induced suppression of precipitation will increase the LWP of a cloud that was originally raining. This presumes that the cloud would otherwise rain in the unperturbed (clean) case. In other words, we do not expect the cloud lifetime effect to impact nonraining clouds, and at least expect a smaller increase in LWP in nonraining clouds.

We separate the cloud scenes in UPCAM and SPCAM based on whether the clouds are raining in the preindustrial simulation and examine how the LWP changes between the preindustrial and present-day simulations. The difference in LWP between the present-day simulation and preindustrial simulation ($\Delta L_{all}$) is estimated using the response of raining cloud ($\Delta L_{rain}$), response of nonraining clouds ($\Delta L_{nonrain}$), and the fraction of raining clouds ($f$):

$$\Delta L_{all} = f \Delta L_{rain} + (1 - f) \Delta L_{nonrain}.$$  

(2)

Even in simulations where winds are nudged to the same large-scale meteorology, the noisy nature of the clouds makes estimating $\Delta L_{rain}$ and $\Delta L_{nonrain}$ difficult, and some approximations and adjustments are required and are described in Appendix B. As a result, slight differences exist between estimates of $\Delta L_{all}$ (solid circles in Figure 6) and the actual spatially averaged change in LWP (open circles in Figure 6), but the decomposition is adequate for us to understand the differences between SPCAM and UPCAM.

Reassuringly, we find that in both UPCAM and SPCAM, the LWP response to aerosol loading is smaller in magnitude for nonraining clouds than in raining clouds, as we would expect. Comparing the UPCAM and SPCAM LWP response, we first find the LWP response in UPCAM is less than in SPCAM for most of the year. In the following, we attempt to more fully understand why UPCAM has a muted LWP response to aerosol compared to SPCAM (blue vs. orange circles) for a large part of the year. Our first finding is that although the average cloud response is lower in UPCAM, the raining cloud response in UPCAM is actually dramatically larger than in SPCAM. In other words, hiding behind the first-order impression of a muted LWP response to aerosol loading is a stronger sensitivity of LWP to increasing aerosol in raining clouds in UPCAM than in SPCAM. Thus, the reason the overall LWP response is weaker in UPCAM must be linked to the other two factors: the response of nonraining clouds and the baseline fraction of raining clouds (or the probability of precipitation). Large-eddy simulations (Ackerman et al., 2004; Bretherton et al., 2007;
Figure 6. Northern Hemisphere (20–50°N) LWP difference over oceans (filled circles) between preindustrial and present-day simulations as a function of calendar month in UPCAM (blue) and SPCAM (orange). Predictions are based on a decomposition after raining (down-pointed triangles) and nonraining cloud LWP responses (up-pointed triangles) are separated and their responses are scaled by the fraction of raining and nonraining clouds as in Equation 2. The vertical lines connect the aggregate response (filled circle) to the corresponding raining and nonraining response in each LWP bin. Open circles indicate actual differences in the LWP between present-day and preindustrial simulations over the same area.

Chen et al., 2011; Dagan et al., 2017; Jiang et al., 2006; Xue & Feingold, 2006) and some observations (Chen et al., 2014; Gryspeerdt et al., 2019; Small et al., 2009; Toll et al., 2017) report the existence of both positive and negative responses of LWP to aerosols, where LWP tends to decrease with increasing aerosols in thin, nonraining clouds. These findings lend support for the overall weak and slightly negative LWP response of nonraining clouds in UPCAM.

If we shift our focus to the baseline fraction of raining clouds in low-lying clouds, we can see from Figure 7 that the fraction of precipitating clouds as a function of LWP is indeed lower in UPCAM than in SPCAM.

Figure 7. Probability of precipitation (using a threshold of 0.6 mm/day) as a function of cloudy-scene liquid water path over Northern Hemisphere (20–50°N) oceans in the month of July. Blue indicates UPCAM and orange indicates SPCAM.
Climate models, in general, show a tendency to overpredict the probability of precipitation (POP; Stephens et al., 2010), and even in SPCAM (Kooperman et al., 2016). Furthermore, Mülmenstädt et al. (2020) point out the importance of establishing the baseline precipitation frequency to better constrain the ACIs. L’Ecuyer et al. (2009) provide such an estimate of POP based on CloudSat, and a comparison of Figure 6 of this study with Figure 1 of L’Ecuyer et al. (2009) suggests that the precipitation fraction in UPCAM is more consistent with the POP from L’Ecuyer et al. (2009). However, differences in averaging length and area of study between L’Ecuyer et al. (2009) and this study make it difficult to conclude strongly which is more realistic.

In summary, the analysis presented in this section and further elaborated in Appendix B provides evidence that the lower increase in LWP with aerosols in UPCAM is due to a weaker LWP increase in nonraining clouds and a small fraction of raining clouds in the baseline climate. Subsequent studies using limited-area simulations will be necessary to address remaining questions, such as whether the smaller domain size or the finer horizontal grids in UPCAM make the LWP response in raining clouds stronger in UPCAM compared to SPCAM.

4. Discussion and Conclusions

We now discuss three implications of our findings. First, the results support the idea that a targeted analysis of ACIs that differentiates the response of raining and nonraining clouds can help us gain a better conceptual understanding of why two different models produce different ACIs. The simulation strategy of nudging large-scale winds inhibits feedbacks of aerosols on circulation but allows a unique test bed for studying ACI. Based on previous global studies (e.g., Wang et al., 2012), we approached the analysis expecting the response of raining clouds to aerosol perturbations to be the largest differentiator of ACI between the models. However, when we separate our analysis into clouds that rain and do not rain, we find that other factors, namely, the baseline fraction of clouds that rain and the response of nonraining clouds, better explain the overall difference in LWP response to aerosols in UPCAM compared to SPCAM. This distinction of ACI in raining and nonraining clouds has been done in previous observational analyses (e.g., Possner et al., 2020; Toll et al., 2017), but here we show how an analogous distinction of ACI in raining versus nonraining clouds can be done even in global models, and proves helpful in understanding emergent ACI effects, provided we nudge the large-scale conditions.

One might then ask, whether SPCAM or UPCAM more realistically capture those factors that we identify as major contributors differentiating the UPCAM from the SPCAM cloud response. LES simulations support a weakly positive or negative response of LWP to increases in aerosols in nonprecipitating clouds, and CloudSat retrievals of the baseline fraction of raining clouds (or probability of precipitation L’Ecuyer et al., 2009) appear to better match UPCAM’s baseline fraction. However, there are many caveats to the comparison with observations, including the difference in horizontal averaging length, which is important to make a consistent assessment of probability of precipitation. The study of L’Ecuyer et al. (2009) also encompasses a larger region over the oceans, compared to the focus of NH clouds in this study. Mülmenstädt et al. (2020) further report the potential importance of differentiating between drizzle and rain to better constrain model behavior. Exploring these are beyond the scope of this study, but highlight observational estimates that will be important for better assessing ACIs in models.

We also find that the LWP response of nonraining clouds in UPCAM is negative, while it is positive in SPCAM. Large-eddy simulations of idealized low-level clouds exhibit a decrease in LWP for nonraining clouds (Ackerman et al., 2004; Chen et al., 2011), supporting the UPCAM response. Observational studies have also reported similar behavior (Chen et al., 2014; Gryspeerdt et al., 2019; Small et al., 2009). Going forward, it will be important to leverage analysis techniques, such as those of Gryspeerdt et al. (2019), to quantify the extent to which the LWP decreases with aerosol in both models and observations, particularly in nonraining clouds. Other metrics, such as precipitation susceptibility, have also been identified to better connect individual processes with the overall LWP response to aerosols (Mann et al., 2014; Sorooshian et al., 2009; Terai et al., 2012; Wang et al., 2012). Here, we view the simulation strategy and analysis in this study as a complementary approach that helps us better confront our cartoon model of the ACIs.

A second implication of our study is that the seasonal cycle in the ACIs can differ between different model configurations (SPCAM and UPCAM). This result, which supports that of Dagan and Stier (2020), highlights
the importance of covering a wide range of meteorological contexts and seasons when comparing ACIs, particularly in high-resolution models where computational costs of running simulations constrains decisions about the variety and duration of simulations.

Third and perhaps most importantly, this study reinforces the need for comparison of ACIs in limited-area high-resolution simulations (LES) with global simulations. This study reveals that by resolving the scales of boundary layer eddies, we arrive at a conceptually different picture of the ACI than one might get from looking at a model that resolves up to the km-scale motions. Even as we move toward storm- or cloud-resolving global simulations (e.g., Sato et al., 2018; Stevens et al., 2019), we are still some years off from resolving the boundary layer eddies in global models (Bellouin et al., 2020; Schneider et al., 2017). There are subgrid turbulence parameterizations that can bridge those subkilometer unresolved scales (Bogenschutz & Krueger, 2013; Larson et al., 2012; Xu & Cheng, 2016; K. Zhang et al., 2017), but their impact on ACI remains to be seen. Furthermore, this study has not explored the sensitivities to microphysical parameters and subgrid-scale schemes that have an impact on rain formation and entrainment mixing (Stevens et al., 2005; van Zanten et al., 2011), both of which impact the overall ACI. Therefore, as increased computational capacities allow for larger domains and longer simulations using large-eddy models, this study stresses the importance of consistently comparing ACI between global and local-scale simulations to gain perspective on areas that need improvement in global models and which will ultimately yield a more reliable global estimate of the radiative impact of ACI.

Appendix A: Difference in One-Moment Versus Two-Moment UPCAM

This study differs from the UPCAM simulations in Parishani et al. (2018) in a number of ways. Whereas the simulations in Parishani et al. (2018) were free-running, used single-moment microphysics, prescribed aerosol concentrations, and were run at 2° × 2° horizontal resolution in the GCM, the simulations in this study had winds nudged every 6 hr, used two-moment microphysics, used the MAM3 prognostic aerosol scheme coupled to cloud-resolving eddy statistics with the Explicit Convection Parameterized Pollution scheme, and were run at 4° × 5° horizontal resolution in the GCM. In addition, because of its large computational cost and especially slow throughput, this model was not tuned in any fashion so that the top-of-atmosphere model matched observations.

Despite this difference, it is still instructive to examine the large-scale climate diagnostics of the model. Table A1 below notes the top-of-atmosphere net shortwave flux (TOA SW) and net longwave flux (TOA LW), the global mean LWP, and the global mean low-cloud fraction. Despite having a smaller coverage of low clouds, the prognostic aerosol version of UPCAM (UP-AER) in this study has more cloud reflection and a larger LWP. For reference, the TOA SW radiation is compared with CERES EBAF v4.1 climatological mean in Figure A1. We find that UP-AER, despite not being tuned and still showing too much absorbed shortwave, improves on the larger solar absorption bias over the stratocumulus region reported in Parishani et al. (2018) and also has fairly small biases over most of the midlatitude oceans. However, the deep convective clouds over the tropical west Pacific are too reflective, leading to a large negative bias in top-of-atmosphere shortwave radiation in UP-AER. The same deep convective regions are also the main source for the negative bias in outgoing TOA LW radiation.

| Model            | TOA SW (W m⁻²) | TOA LW (W m⁻²) | LWP (g m⁻²) | Low-cloud fraction (%) |
|------------------|----------------|----------------|-------------|------------------------|
| UP-AER (this study) | 227            | 218            | 59.0 [67.3ᵃ] | 37                     |
| UPCAM (P18ᵇ)     | 245            | 240            | 54.3        | 48                     |
| Satellite obs    | 241            | 240            | 82.1ᵇ       | N/A                    |

ᵃMean LWP averaged only over ocean.ᵇParishani et al. (2018).
Appendix B: Separating Out the Aerosol-Mediated Cloud Response in Raining and Nonraining Clouds

In this section we explain how we calculate the aerosol-cloud adjustment in raining and nonraining clouds. We first separate snapshots of cloudy GCM grid columns in the preindustrial simulation based on whether or not they are raining using a rain threshold of 0.6 mm day\(^{-1}\) (Wang et al., 2012). Our results are largely insensitive whether we divide or multiply our threshold by a factor of four. Since meteorology is nudged identically, each snapshot in the preindustrial simulation has a corresponding snapshot in the present-day simulation, where the geographic location, time of day, and large-scale meteorology match with those of the preindustrial simulation.

We might naively then take the cloud response to aerosol perturbations to be equal to the difference in the LWP between the present-day and preindustrial snapshot. However, that difference does not take into account a level of stochasticity (randomness) inherent in all clouds, including superparameterized clouds (Jones et al., 2019).

Because of this stochasticity, even if were to examine two simulations with the same aerosol emission scenarios and meteorological nudging, there will be some LWP cloud difference in each snapshot comparison. For example, if the LWP is anomalously higher in the first simulation it will tend toward the mean in the second simulation and produce a negative change in LWP. Now when we separate the clouds into those that are raining and those that are not, we end up selecting clouds with higher anomalous cloud LWP. Therefore, if we were then to look at the LWP change in two simulations with the same LWP distribution, we would find that the change in LWP of raining clouds is negative, while the change of nonraining clouds is positive. Note that this negative response of raining clouds is purely due to the stochasticity of clouds and does not have any physical mechanism behind it.

The extent to which we will see this effect is a function of both the difference in mean LWP of raining and nonraining clouds but also a function of the correlation between the LWP in the first and second simulation. If the LWP in the first simulation perfectly matches the LWP in the second simulation, then we would not see this effect. On the other hand, if it happened that the geographic location, time of day, and large-scale meteorology has no impact on LWP, we would see zero correlation in the LWP of the first and second simulations and this regression to the mean effect will be strongest.
Figure B1. The difference in liquid water path (circles) between present-day and preindustrial simulations as a function of preindustrial LWP in UPCAM (blue) and SPCAM (orange). Each liquid water path response is based on a decomposition of raining (down-pointed triangles) and nonraining cloud LWP responses (up-pointed triangles), scaled by the fraction of raining and nonraining clouds as in Equation 2. The vertical lines connect the aggregate response (filled circle) to the corresponding raining and nonraining response in each LWP bin. All 12 calendar months are shown.

To take into account the impact of stochasticity on our analysis, we therefore apply a correction term that is a function of both the LWP anomaly for a snapshot $x (L_{x,PI} - L_{x,PD})$ and the correlation between the snapshots from the present-day and preindustrial simulations ($r(L_{PI}, L_{PD})$). Therefore, the corrected LWP change ($\Delta L_x$) is formulated as

$$\Delta L_x = L_{x,PD} - L_{x,PI} + (L_{x,PI} - \overline{L_{all,PI}})(1 - r(L_{PI}, L_{PD})).$$

(B1)

In this way, the correction factor $(L_{x,PI} - \overline{L_{all,PI}})(1 - r(L_{PI}, L_{PD}))$ will go to 0 as the stochasticity goes to 0 and $(r(L_{PI}, L_{PD}))$ goes to 1. An advantage of this correction is that when all instances are aggregated, they sum to 0. Using this corrected LWP response for each snapshot, we aggregate all the raining and nonraining cloud instances from the preindustrial simulation to produce a total monthly-mean $\Delta L_{all}$ as a function of the mean raining cloud response $\Delta L_{rain}$ and mean nonraining cloud response $\Delta L_{nonrain}$ as in Equation 2.

Figure B1 shows how $\Delta L_{all}$, $\Delta L_{rain}$, and $\Delta L_{nonrain}$ vary as a function of LWP in UPCAM and SPCAM. Matching expectation from our conceptual understanding, we find that the LWP response in raining clouds is more positive than the response in nonraining clouds in both SPCAM and UPCAM across all months and they peak in intermediate values of LWP. Matching the monthly means in Figure 6, we also find that $\Delta L_{rain}$ in UPCAM tends to lie above $\Delta L_{rain}$ in SPCAM, which indicates that the raining cloud response is not the reason for the lower overall LWP response in UPCAM. Instead, it is UPCAM’s lower $\Delta L_{nonrain}$ and smaller $f$. 
Data Availability Statement

The daily cloud droplet number concentration retrievals cited in this study and in Grosvenor et al. (2018) can be retrieved at the following site (https://zenodo.org/record/3968813#.XySdtvhKg0o). Processed model output relevant for this data can be found here: https://zenodo.org/record/3968813#.XySdtvhKg0o.
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