SCM Simulations of Tropical Ice Clouds Using Observationally Based Parameterizations of Microphysics

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ABSTRACT

A new bulk parameterization of the dependence of ice cloud effective radius ($r_e$) on ice water content (IWC) is developed using in situ observations of the size and shape of ice crystals in tropical anvils. This work extends previous parameterizations because information about the number, size, and shape of ice crystals with diameters smaller than 100 $\mu$m is included and in that a range of possible fit coefficients, rather than single values, is given to reflect the fact that $r_e$ can vary significantly about its mean parameterized value.

The parameterization is implemented in the Scripps single column model (SCM), and simulations of tropical clouds over the Atmospheric Radiation Measurement (ARM) program’s tropical western Pacific (TWP) site and over the Tropical Ocean Global Atmosphere Coupled Ocean–Atmosphere Response Experiment (TOGA COARE) domain are conducted. Sensitivity studies determine how the range of possible fit coefficients, which reflects the uncertainty in the parameterization of $r_e$, relates to uncertainties in modeled cloud radiative forcings (CRFs). When $r_e$ is chosen one or two standard deviations higher or lower than the mean parameterized value, temporally averaged shortwave CRFs can differ by up to 17.7 W m$^{-2}$ from that value estimated from the mean parameterized $r_e$, the difference depending on the time period and location; differences in longwave CRFs are substantially less. When other uncertainties in the parameterization are accounted for, such as those based on the observed numbers of smaller crystals, CRFs can differ by up to 25 W m$^{-2}$ from that determined by the base parameterization. When $r_e$ is randomly chosen for each simulation time within one or two standard deviations of the most likely $r_e$ for that IWC, shortwave CRFs can still differ from that of the base simulation by up to 13.9 W m$^{-2}$, with an enhancement of shortwave reflection of up to 4.9 W m$^{-2}$ observed on average. Therefore, the average of a series of such simulations may not equal a simulation of average conditions, a finding that may have important ramifications.

Both interactive simulations, where changes in cloud heating rates feed back upon predicted cloud masses, and noninteractive simulations, where changes in heating rate do not feed back upon cloud mass, are performed in order to determine how and why different parameterizations affect the CRFs. It is shown that differences in longwave heating rates, associated with different versions of the parameterization, alter the mass of ice and liquid water produced at various levels, this change in cloud mass in turn affects the CRF. This change can either amplify or reduce the change in CRF associated with the more direct effect of varying the $r_e$ parameterization, namely, that smaller particles reflect more shortwave radiation given the same mass content. The amount of liquid water present in low clouds is an important indicator of whether changing ice cloud microphysical properties will have an important effect on CRF.

1. Introduction

Accurate parameterizations of cloud effective radius ($r_e$) are crucial for accurate estimates of upwelling and downwelling radiative fluxes and of cloud radiative forcing in modeling studies. This dependence is seen by examining the response of specific general circulation models (GCMs) to changes in the representation of cloud properties. For example, changes made in the European Centre for Medium-Range Weather Forecasts GCM between 1990 and 1996, to correct for an improper choice of prescribed cloud droplet radius, changed the cloud “feedback” parameter from strongly positive to slightly positive (Cess et al. 1996). The Goddard Institute for Space Studies GCM has also changed from a strong positive feedback due to a large decrease in shortwave (SW) feedback; the new slightly negative feedback is produced by a dramatic increase, for a warmer climate, in both the cloud water content (brighter clouds) and the amount of tropical cumulus anvils. Iacobellis
and Somerville (2000) also found that modeled radiative fluxes were sensitive to the specification of \( r_e \), and that the most realistic vertical distribution of clouds was obtained from that experiment including the most complete representation of cloud microphysics.

Based on in situ observations of the size and shape of ice crystals in blow-off anvils associated with deep convection in the Tropics, which were acquired during the Central Equatorial Pacific Experiment (CEPEX; McFarquhar and Heymsfield, 1997), a new bulk parameterization of the dependence of ice crystal effective radius \( (r_e) \) on ice water content \( (IWC) \) and temperature is developed here. The parameterization includes uncertainty estimates so that sensitivities of model parameters to possible variations in \( r_e \) can be computed. The use of this parameterization is suitable for models with a prognostic scheme for IWC, but without explicit prediction of other moments of the ice crystal distribution. For tropical simulations, its use should result in modeled ice clouds that more closely resemble those observed than the use of schemes that assume a constant \( r_e \) or a simple dependence on temperature (e.g., Kiehl et al., 1998).

The size and shape distributions of ice crystals used to calculate \( r_e \) are derived following the work of McFarquhar et al. (2002), who introduced a new parameterization for the single-scattering radiative properties of ice clouds based upon observations obtained during CEPEX. These distributions differ from those calculated using McFarquhar and Heymsfield’s (1997) parameterization in three important ways. First, information is included about the potential variance of the parameterization coefficients that describe the number and size of small crystals, with melted equivalent diameters smaller than 100 \( \mu m \). Second, instead of using a sphere to represent the shape of small ice crystals, the shape is described in terms of expansions of Chebyshev polynomials. Finally, a neural network classification scheme (McFarquhar et al. 1999) is used to determine the shape of each ice crystal image with a size larger than 100 \( \mu m \), and hence to estimate its mass. For the purpose of this study, \( r_e \) is defined as proportional to the total mass of the ice crystals divided by the total projected area, following Fu (1996). Hence, with the three-dimensional shapes estimated from the neural network scheme and the ice crystal size distributions, it is possible to develop a parameterization of \( r_e \) complete with uncertainty estimates.

The sensitivities of modeled radiative fluxes and modeled cloud fields to the use of this new observationally based parameterization scheme and to previously published parameterization schemes are investigated here. This is done by incorporating various parameterization schemes into the Scripps single column model (SCM). Because results produced by an entire climate model are quite complex in nature and hence difficult to interpret, an SCM is convenient for this study because it is more straightforward in determining how uncertainties in the parameterizations affect the modeled radiative and cloud fields. Further, because SCMs are much less time consuming and computationally inexpensive, a greater range of experiments can be performed. An SCM is a single vertical column of a GCM, containing a full set of parameterizations of subgrid physical processes. Observations are used to specify what occurs in neighboring columns, and results at a simulation time are used to predict new values of prognostic variables for the next simulation time. Petch (1998) has previously used an SCM to investigate improved radiative transfer calculations from information provided by bulk microphysical schemes.

Experiments are conducted not only to illustrate the sensitivity of modeled cloud and radiative fields to \( r_e \), but also to determine the mechanisms by which the different parameterization schemes affect these fields. Both interactive simulations, where changes in cloud heating rates feed back upon cloud mass, and noninteractive simulations, where they do not, are performed.

The remainder of this paper is organized as follows. Section 2 describes the Scripps SCM used to simulate the tropical environment. Section 3 provides a derivation of the new observationally based parameterization scheme and outlines the series of sensitivity experiments that are conducted; a brief description of the shortwave and longwave radiative parameterization schemes used is also provided. Section 4 describes the model results, and section 5 discusses the significance of the findings, and compares the results with those obtained during previous studies.

### 2. Description of Scripps SCM

The model used in this study is an SCM that has evolved from the one described by Iacobellis and Somerville (1991a,b). Because Iacobellis and Somerville (2000) describe the implementation of this model using observational data collected during the Tropical Ocean Global Atmosphere Coupled Ocean–Atmosphere Response Experiment (TOGA COARE), only the most salient features are summarized here.

The input to the SCM is an initial state plus time-dependent advection terms in the conservation equations, provided at all layers. Time-dependent outputs include temperature and moisture profiles, clouds and their radiative properties, diabatic heating terms, surface energy balance components, and hydrologic cycle elements. From this information, vertical profiles of radiative heating and cooling can be derived. Following Iacobellis and Somerville (2000), this version of the SCM uses a time step of 7.5 min, an ocean surface albedo of 0.05, and a diurnally varying solar signal dependent on latitude and time of the year. The cloud ice/water content and fractional cloud cover are prognostic variables in the version of the SCM used, and are calculated following Tiedtke (1993). The longwave (LW) radiation parameterization of Mlawer et al. (1997) and
the relaxed Arakawa and Schubert (1974) cumulus convection parameterization are used. Maximum overlap of clouds is assumed in all experiments because of the relatively high vertical resolution and because the prevalence of deep convection in the Tropics suggests that the cloud layers could be correlated in the vertical; other investigators (e.g., Jacob and Klein 1999; Collins 2001) have examined the merits of different overlap schemes, but such issues are beyond the scope of this study. The SCM is operated in a “relaxation mode,” where the temperature and humidity profiles are relaxed to the observed profiles using a time constant of 24 h. All other nonspecified options follow those used by Iacobellis and Somerville (2000).

Two separate sets of simulations are conducted. One set of simulations is conducted using data collected during TOGA COARE to force the SCM for the same 39-day period (18 December 1992–23 January 1993) simulated by Iacobellis and Somerville (2000). This simulation represents the area between approximately 2°N and 5°S, 150° and 160°E. Another set of simulations describes, and is based upon, conditions measured at the Atmospheric Radiation Measurement (ARM) program’s tropical western Pacific (TWP) site, located in the area roughly between 10°N and 10°S from Indonesia to near Christmas Island in the warm pool region. A period between 9 August 2000 and 8 September 2000 is chosen for simulation because data collected by the millimeter-wavelength cloud radar (MMCPR) at Nauru Island (167°E, 2°S) indicated that there was moderate cirrus activity during this time. Further, SCM simulations conducted over the entire second half of 2000 and the entire 2001 time frame indicated that high cloud cover and high cloud optical depth were near a maximum for this time period. The forcing data for this simulation was derived from the National Centers for Environment Prediction (NCEP) Global Spectral Model (GSM). Since these data are from a forcing model, rather than from observations as for the TOGA COARE period, the forcing might not be as accurate; however, preliminary indications are that the SCM is performing adequately. Investigations of the sensitivities of model performance to forcing data and advective tendencies are beyond the scope of this study.

A vertical resolution of 53 layers is used for these simulations because a finer resolution allows more details of the microphysical–radiative interactions to be resolved. Lane et al. (2000) investigated how changes in SCM vertical resolution affected the cloud and radiation parameterizations. They found that even at the highest vertical resolution of 60 layers, the model results did not converge with increasing resolution and that there were systematic differences between model results and observations acquired during intensive observation periods at the ARM sites. Because of this and because it is difficult to determine how well the available observations represent an entire GCM grid box, the focus of this study is simply to determine the sensitivities of model output to different microphysical parameterization schemes.

Because the SCM simulates the temporal evolution of a nonlinear system, it must be determined whether differences between simulations are due to variations in microphysical representations or due to the chaotic nature of the dynamical system. Our past experience has shown that there is little sensitivity to initial condition variations and that there is better agreement with observations when the SCM is run in a relaxation mode (see also Ghan et al. 2000). To verify the lack of dependence of estimated cloud forcings on variations in initial conditions, an ensemble of runs with both constant microphysics and random perturbations to the initial temperature and humidity profiles, was made. The magnitude of the perturbations was up to 1°C in temperature and up to 5% of the humidity value, matching perturbations used in past ensemble studies. Although the model exhibited some sensitivity to these perturbations, with a standard deviation in the top-of-the-atmosphere (TOA) SW cloud radiative forcing (CRF) of 4.4 W m⁻², the mean SW CRFs calculated from the ensemble runs differed by less than 0.5 W m⁻² from the simulation without perturbations. Therefore, any systematic change associated with a variation in the microphysical parameterization should not be associated with the chaotic nature of the model.

3. Microphysical parameterization

There are basically two different approaches used to improve the representations of microphysics in large-scale models. In the first, more details of the physical mechanisms responsible for the evolution of various moments of liquid and ice phase particle size distributions are added to model equations. However, because of complex nonlinear interactions occurring in clouds, adding extra terms and equations may not result in more accurate simulations if other terms of similar importance are identically not included. In addition, there is uncertainty as to how to represent some of these important processes. Hence, an alternate approach is sometimes used whereby observed relationships are used to represent functional dependences between moments of the size distributions and other variables. This approach only works when these relationships are applied under conditions similar to the conditions under which the observations were obtained. It is this approach that is followed in this paper.

The microphysical parameterizations used in this study involve diagnostic relationships for $r_i$ in terms of IWC and temperature. McFarquhar and Heymsfield (1998) review several different definitions of $r_i$ that have been used and conclude that the use of definitions that are proportional to the ratio between IWC and cross-sectional area, $A_i$ (e.g., Francis et al. 1994; Fu 1996), are most useful. Following Fu (1996), it is assumed that
Table 1 summarizes previously published parameterization schemes for \( r_e \) as function of temperature, IWC, or both. Relations may differ from originally published schemes because they have been adjusted, as shown, to ensure a consistent definition of \( r_e \) (Fu 1996) is used for all schemes: \( T \) in °C, \( T_k \) in K; \( r_e, r_m \) in μm; IWC in g m\(^{-3}\); \( M \) in g; \( M/A \) in g cm\(^{-1}\); \( L \) in mm.

<table>
<thead>
<tr>
<th>Scheme</th>
<th>Equations</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>( r_e = 10 )</td>
</tr>
<tr>
<td>Suzuki et al. (1993)</td>
<td>( r_{e_0} = 0.71T + 61.29 )</td>
</tr>
<tr>
<td></td>
<td>( L = r_{e_0}/238, M = \frac{4}{3}\pi r_{e_0}^3/10^{12}, \rho = 0.78 \text{ g cm}^{-3} )</td>
</tr>
<tr>
<td></td>
<td>( M/A ) (Heymsfield and Iaquinta 2000)</td>
</tr>
<tr>
<td></td>
<td>( r_e = 10^{0.78}/M/A )</td>
</tr>
<tr>
<td>Ou and Liou (1995)</td>
<td>( D_1 = 326.3 + 12.42T + 0.197T^2 + 0.00127T^3 )</td>
</tr>
<tr>
<td></td>
<td>( r_e = -1.56 + 0.388D_1 + 0.00051D_1^2 )</td>
</tr>
<tr>
<td>McFarlane et al. (1992)</td>
<td>( L = 0.698 + 0.366LIWC + 0.122LIWC^2 + 0.0136LIWC^3, LIWC = \log_{10}(IWC) )</td>
</tr>
<tr>
<td></td>
<td>( r_e = \frac{4\sqrt{3}}{9} \sqrt{1 - \exp(-10/Ld)}, c = 63.9 \mu m, d = 0.0075 \mu m^{-1} )</td>
</tr>
<tr>
<td>Wyser (1998)</td>
<td>( b = -2.0 + 0.001T^3 \log_{10}(IWC/50) )</td>
</tr>
<tr>
<td></td>
<td>( r_{e_0} = 377.4 + 203.6b \pm 37.91b^2 + 2.369b^3 )</td>
</tr>
<tr>
<td></td>
<td>( r_{e_0} = r_{e_0}/N_{\text{mean}} N_{\text{mean}} = \frac{\sqrt{3} + 4}{3\sqrt{3}} )</td>
</tr>
<tr>
<td></td>
<td>( r_e = \frac{\sqrt{3}}{r_{e_0}} )</td>
</tr>
<tr>
<td>McFarquhar (2001)</td>
<td>( r_e = \frac{\sqrt{3}}{3\rho_i A_r}, ) ( a_i, b_i, c_i, d_i ) functions of ( T )</td>
</tr>
</tbody>
</table>

where \( \rho_i \) is the density of ice. This definition is compatible with the single-scattering radiative parameterizations used in this study.

Table 1 summarizes previously published microphysical parameterization schemes. These parameterizations range from an assumption of a constant \( r_e \) of 10 μm, to calculated dependences on temperature (Suzuki et al. 1993; Ou and Liou 1995), on IWC (McFarlane et al. 1992), and on both IWC and temperature (Wyser 1998; McFarquhar 2001). Figure 1 shows the variation of \( r_e \) with temperature and IWC, showing that substantial differences between schemes exist. Note that all plotted \( r_e \) are defined following Fu’s (1996) definition and that many of the equations listed in Table 1 are different from those listed in the original references because of differences in \( r_{e_0} \) definitions. Since other definitions of \( r_e \) were used by other authors, including definitions proportional to the third moment of the volume-equivalent particle radius divided by the second moment (Suzuki et al. 1993), to the cross-section weighted mean radius (Wyser 1998), and to the third moment of the area-equivalent particle radius divided by the second moment (Ebert and Curry 1992), a conversion to Fu’s (1996) \( r_e \) definition must be made.

Such conversions are nontrivial and require additional information about the lengths, aspect ratios, masses, and projected areas of different crystal habits. When converting between \( r_e \) definitions, information about ice crystal geometries from Heymsfield (1972, 1977), and Heymsfield and Iaquinta (2000) was used. Table 1 summarizes the manner in which these conversions are performed. For example, to convert Suzuki et al.’s (1993) \( r_{e_0} \), mass–area ratios derived by Heymsfield and Iaquinta (2000) for bullet rosettes and columns (the crystal shapes noted by Suzuki et al. 1993) are combined with mass relations in terms of crystal length to calculate the projected areas of the ice crystals. The ratio of mass divided by projected area, multiplied by a constant, then gives \( r_e \) following Fu’s (1996) definition.

McFarquhar (2001) describes a parameterization scheme for \( r_e \) in terms of IWC and temperature based upon a straightforward application of McFarquhar and Heymsfield’s (1997) parameterization. A new parameterization, based upon an improved treatment of small ice crystals, is derived here. The modifications that are made to the McFarquhar (2001) scheme include the use of randomized parameterization coefficients describing the numbers and sizes of small crystals, the use of Chebyshev polynomials to describe the shapes of small crystals, and the use of a neural network habit classification scheme (McFarquhar et al. 1999) to describe the shapes of the larger crystals.

Following McFarquhar et al. (2002), habit-dependent size distributions for crystals with melted equivalent diameters, \( D_m \), greater than 100 μm are derived by applying McFarquhar et al.’s (1999) neural network classification scheme to images recorded by a two-dimensional cloud probe (2DC). The numbers and sizes of smaller crystals, henceforth defined as crystals with \( D_m \) smaller than 100 μm (which corresponds to maximum dimensions smaller than approximately 120 μm for the quasi-circular small particles), are determined using McFarquhar and Heymsfield’s (1997) parameterization scheme with coefficients randomly chosen from the sur-
Figure 1. Variation of $r_e$ with IWC from previously published schemes, $r_e$ defined following Fu (1996). Plotted values may differ from previously published values due to $r_e$ conversions. Some schemes are plotted multiple times corresponding to varying temperature.

Face of equally realizable solutions defined by McFarquhar et al. (2002). Even though 90% of the 11,633 small crystals used to develop the small crystal parameterization scheme were manually identified as spherical or quasi-spherical, Figs. 22 and 23 of McFarquhar and Heymsfield (1996) show that many of these crystals are not exactly circular in shape. Therefore, following McFarquhar et al. (2002), the shape of these particles is represented using eighth-order Chebyshev polynomials with projected areas equal to those of the observed particles.

Figure 2 plots $r_e$, calculated using the composite size distributions defined above, as a function of IWC. McFarquhar’s (2001) parameterization scheme for $r_e$ is plotted for comparison. The large scatter in the $r_e$ data points occurs due to the stochastic application of the small crystal parameterization. On average, the $r_e$ calculated using Chebyshev particles to describe the small ice particles are smaller than those calculated using spherical particles to describe the small ice particles because, given the same mass, Chebyshev particles have larger areas, and hence smaller mass-area ratios leading to lower calculated $r_e$. This is especially true for small IWCs. For IWCs larger than 0.5 g m$^{-3}$, the new calculations give average $r_e$ values larger than those determined using the McFarquhar (2001) parameterization because of a change in crystal geometry used to represent large crystals from that assumed by McFarquhar and Heymsfield (1997).

When applying the new form of the parameterization in the SCM, a multivariate dependence of $r_e$ on both temperature and IWC was not considered. However, $r_e$ implicitly depends on temperature, and decreases with temperature, because IWC decreases with temperature on average (Heymsfield and McFarquhar 2002). Multivariate dependence is not considered for the following reasons: the scatter in the $r_e$ points is much larger than can be accounted for by a simple temperature dependence; the temperature-dependent curves only differ substantially for larger IWCs, where the data may be less reliable; and crossovers between fit coefficients at different temperatures could cause artificial jumps in vertical profiles of radiative or latent heating and cooling. The solid line represents the best fit of $r_e$ as a function of IWC, obtained by applying matrix inversion to mean $r_e$ values within a number of IWC bins, where

$$r_e = 10^a + b \log(z) + c \log(z)^2,$$

with $z = \text{IWC}/\text{IWC}_0$, $\text{IWC}_0 = 1.0$ g m$^{-3}$, and $a$, $b$, and $c$ are the coefficients of the fit listed in Table 2. The thin dashed lines in Fig. 2 represent fits obtained for data points that are one and two standard deviations
**Table 2.** Coefficients $a$, $b$, $c$ for use in Eq. (2). Three different cases (base, minimize small crystals, maximize small crystals) shown, as obtained from in situ microphysical data and varying assumptions about numbers of ice crystals smaller than 100 $\mu$m. Within each case, different values represent most likely $r_e$ ($r_{e,\text{best}}$), and values 1 $\sigma$ and 2 $\sigma$ larger and smaller than $r_{e,\text{best}}$.

<table>
<thead>
<tr>
<th>Case</th>
<th>Fit description</th>
<th>$a$</th>
<th>$b$</th>
<th>$c$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Base case (Fig. 2)</td>
<td>$r_e = r_{e,\text{best}}$</td>
<td>1.784 49</td>
<td>0.281 301</td>
<td>0.017 716 6</td>
</tr>
<tr>
<td></td>
<td>$r_e = r_{e,\text{best}} + 1 \sigma$</td>
<td>1.871 55</td>
<td>0.320 616</td>
<td>0.025 649 1</td>
</tr>
<tr>
<td></td>
<td>$r_e = r_{e,\text{best}} + 2 \sigma$</td>
<td>1.945 32</td>
<td>0.351 843</td>
<td>0.031 974 6</td>
</tr>
<tr>
<td></td>
<td>$r_e = r_{e,\text{best}} - 1 \sigma$</td>
<td>1.678 48</td>
<td>0.229 889</td>
<td>0.007 397 41</td>
</tr>
<tr>
<td></td>
<td>$r_e = r_{e,\text{best}} - 2 \sigma$</td>
<td>1.543 53</td>
<td>0.159 153</td>
<td>-0.006 704 81</td>
</tr>
<tr>
<td>Minimize small crystals (Fig. 3)</td>
<td>$r_e = r_{e,\text{best}}$</td>
<td>1.901 44</td>
<td>0.372 406</td>
<td>0.033 905 6</td>
</tr>
<tr>
<td></td>
<td>$r_e = r_{e,\text{best}} + 1 \sigma$</td>
<td>2.002 62</td>
<td>0.421 939</td>
<td>0.043 496 0</td>
</tr>
<tr>
<td></td>
<td>$r_e = r_{e,\text{best}} + 2 \sigma$</td>
<td>2.086 56</td>
<td>0.460 521</td>
<td>0.051 014 9</td>
</tr>
<tr>
<td></td>
<td>$r_e = r_{e,\text{best}} - 1 \sigma$</td>
<td>1.774 46</td>
<td>0.305 822</td>
<td>0.021 123 7</td>
</tr>
<tr>
<td></td>
<td>$r_e = r_{e,\text{best}} - 2 \sigma$</td>
<td>1.604 29</td>
<td>0.209 487</td>
<td>0.002 849 92</td>
</tr>
<tr>
<td>Maximize small crystals (Fig. 4)</td>
<td>$r_e = r_{e,\text{best}}$</td>
<td>1.648 31</td>
<td>0.319 807</td>
<td>0.029 311 6</td>
</tr>
<tr>
<td></td>
<td>$r_e = r_{e,\text{best}} + 1 \sigma$</td>
<td>1.756 12</td>
<td>0.310 124</td>
<td>0.026 348 5</td>
</tr>
<tr>
<td></td>
<td>$r_e = r_{e,\text{best}} + 2 \sigma$</td>
<td>1.841 51</td>
<td>0.302 976</td>
<td>0.024 190 4</td>
</tr>
<tr>
<td></td>
<td>$r_e = r_{e,\text{best}} - 1 \sigma$</td>
<td>1.500 76</td>
<td>0.333 535</td>
<td>0.033 656 4</td>
</tr>
<tr>
<td></td>
<td>$r_e = r_{e,\text{best}} - 2 \sigma$</td>
<td>1.257 09</td>
<td>0.351 214</td>
<td>0.040 324 5</td>
</tr>
</tbody>
</table>
greater than or less than the mean $r_e$ for each IWC bin. These extreme cases will be used to examine the dependence of the SCM results on the $r_e$ parameterizations.

Other uncertainties in the derivation of Eq. (2) are assumptions about the number, mass, and size distributions of small ice crystals. Although the stochastic application of the parameterizations somewhat accounts for these uncertainties, it must be acknowledged that the McFarquhar and Heymsfield (1997) parameterization was based on a limited set of data and that no measurements of small crystals were obtained for IWCs greater than 0.1 g m$^{-3}$. To investigate uncertainties associated with extrapolating the measured results to IWCs greater than 0.1 g m$^{-3}$, a sensitivity study is conducted where the mass in small crystals, IWC$_s$, is set using McFarquhar and Heymsfield’s (1997) parameterization scheme as before, except that the total IWC is assumed to be 0.1 g m$^{-3}$. Therefore,

$$\text{IWC}_s = a(0.1)^b,$$  \hspace{1cm} (3)

where $a$ and $b$ are randomly chosen from the surface of equally plausible solutions as before. This provides an upper bound on $r_e$ by minimizing contributions of small crystals.

Figure 3 shows how $r_e$, calculated in this manner, varies as a function of IWC, with the coefficients of the fit listed in Table 2. The data are different from those in Fig. 2 only for IWCs greater than 0.1 g m$^{-3}$. For IWCs between 0.1 and 0.2 g m$^{-3}$, the differences between the two schemes are not substantial with mean $r_e$ of 37.2 and 39.8 μm for the base scheme and for the scheme minimizing small crystals, respectively. However, for IWCs between 0.5 and 1.0 g m$^{-3}$, the differences are more substantial with mean $r_e$ of 46.0 and 63.1 μm for the respective schemes. For large IWCs, the numbers of large crystals might also be underestimated from the data since the 2DC probe, used to obtain the data, does not measure ice crystals with maximum dimensions larger than about 1 mm. By examining mass distribution functions, McFarquhar and Heymsfield (1996) showed that this omission would not be a problem for IWCs less than 0.1 g m$^{-3}$.

In another sensitivity study, the contributions of small crystals were maximized by using the size distributions...
measured by a forward scattering spectrometer probe (FSSP) installed on the same aircraft as the 2DC used to measure ice crystals with \( D_m \) larger than 100 \( \mu m \); FSSP measurements are most likely unreliable in ice clouds with substantial numbers of large ice crystals, but are useful in that they represent an upper bound for small crystal numbers (McFarquhar et al. 2002). Figure 4 shows how \( r_e \) varies as a function of IWC and Table 2 lists the fit coefficients. The estimated \( r_e \) are much smaller, with mean values of 26.1 and 31.1 \( \mu m \) for IWCs between 0.1 and 0.2 \( g/m^3 \) and between 0.2 and 0.5 \( g/m^3 \), respectively, compared to 37.2 and 46.0 \( \mu m \) for the base case.

Table 3 summarizes the different sensitivity studies conducted with the Scripps SCM. All sensitivity studies are performed for both the TOGA COARE and ARM TWP time periods to test the schemes under two sets of conditions. The first series of sensitivity studies involves previously published schemes, and the second series involves parameterizations, and associated uncertainties, developed using the in situ measured CEPEX data. The third series examines effects associated with varying the numbers of small crystals, which hence examines the impacts of larger and smaller \( r_e \) values.

For all simulations, a modified form of Ebert and Curry’s (1992, hereafter EC92), shortwave radiative parameterization scheme is used. The appendix describes a new version of EC92 which is based upon a generalized effective radius (Fu 1996), rather than the \( r_e \) definition originally used by EC92. Only the \( r_e \) values have been shifted in the modified scheme; the radiative properties, based on assumptions of hexagonal columns, remain the same. This new version of EC92 was produced because otherwise some of the conversions between \( r_e \) schemes could result in unrealistically large asymmetry parameters or single-scattering albedos. The longwave emissivity is defined following the expression of Platt and Harshvardhan (1988). Future studies will concentrate on how different longwave and shortwave radiative parameterization schemes affect modeled cloud properties.

4. Model results

a. Approach

Two separate sets of simulations are conducted, covering the TOGA COARE domain and covering the ARM TWP domain. Two studies are also conducted for each set of simulations, the first of which is henceforth called interactive microphysics and the second of which is henceforth called noninteractive microphysics. With interactive microphysics, ice and cloud water path vary according to the prognostic equations in the model; differences in microphysical properties produce changes in heating profiles, which in turn alter the ice and cloud water amounts. Therefore, the simulations are interactive. In such simulations, small variations in IWC produced by different parameterization schemes quickly amplify so that any difference in parameterization schemes is quickly dominated by differences in IWC. However, unlike the differences associated with randomly induced perturbations in the temperature and moisture fields described earlier, the differences between simulations with varying microphysics are systematic because changes in \( r_e \) induce nonrandom amounts of extra heating or cooling in the clouds.

In the second series, ice and cloud water path are forced to that value predicted by the base simulation for each series (i.e., 1a, 2a, and 3a); these simulations are noninteractive because differences in radiative heating rates do not feed back upon the ice and cloud water amounts predicted by the model. The first studies help determine the net uncertainties associated with the different parameterization schemes, whereas the second studies help to better understand which factors cause variations in predicted cloud and radiative properties.

b. Temporal variation of quantities

Because many qualitative trends noted in the sensitivity of radiative fluxes to the use of different microphysical parameterizations are similar for the ARM TWP and TOGA COARE domains, only the ARM TWP simulations are shown and discussed in detail. Figure 5 illustrates the variation of the SW and LW CRF at TOA as a function of time for the simulation covering the ARM TWP domain, together with the temporal variation of cloud cover and precipitation. Figure 5e compares the simulated downwelling shortwave flux (DWSWF), with observations of the same quantity obtained by pyranometers at Nauru Island, Manus Island (2°S, 147°E), and from seven moorings located between 8°N and 8°S at 165°E. The different lines represent simulations performed with different \( a, b, \) and \( c \) coefficients in Eq. (2), defining the base case in Fig. 2 and Table 2, and defining \( r_e \) values one and two standard deviations lower and higher than the base values. The thick line represents the simulation performed assuming a constant \( r_e \) of 10 \( \mu m \). Although \( r_e \) as small as 10 \( \mu m \) are not frequently encountered in ice clouds, these simulations are conducted because it represents an extreme lower bound for \( r_e \) and because it allows for easy comparison of our results with some earlier studies that used such values; for example, Kiehl et al. (1998) assumed \( r_e \) for ice clouds varied between 10 and 30 \( \mu m \) depending on pressure. All plotted variables are 24-h average running means, except for SW CRFs, which are plotted as daily averages. The smoothing prohibits excessive scattering in the results.

Substantial variations in SW CRF are seen, together with variations in cloud cover that are most noticeable for lower cloud covers. The time period between 24 and 27 August is an example of a large difference in cloud cover, and the varying cloud cover may cause the differences in SW CRF. There are also time periods when
FIG. 4. As in Fig. 2, except contributions of small crystals are maximized by assuming that FSSP adequately characterizes the numbers and sizes of small crystals (see text for details).

TABLE 3. Summary of sensitivity studies conducted using different representations of $r_e$. Some simulations conducted multiple times with randomly chosen coefficients.

<table>
<thead>
<tr>
<th>Series</th>
<th>Sensitivity investigated</th>
<th>Simulation</th>
</tr>
</thead>
</table>
| 1      | Previously published schemes | (1a) $r_e = 10 \, \mu m$  
|        |                          | (1b) Suzuki et al. (1993)  
|        |                          | (1c) Ou and Liou (1995)  
|        |                          | (1d) Wyser (1993)  
|        |                          | (1e) McFarquhar (2001)  
|        |                          | (2a) $r_{e,\text{best}}$  
|        |                          | (2b) $1 \, \sigma$ lower than $r_{e,\text{best}}$  
|        |                          | (2c) $2 \, \sigma$ lower than $r_{e,\text{best}}$  
|        |                          | (2d) $1 \, \sigma$ higher than $r_{e,\text{best}}$  
|        |                          | (2e) $2 \, \sigma$ higher than $r_{e,\text{best}}$  
|        |                          | (2f) $r_e$ randomly chosen $\pm 1 \, \sigma$  
|        |                          | (2g) $r_e$ randomly chosen $\pm 2 \, \sigma$  
| 2      | McFarquhar et al. (2002) $r_e$ derivation |  
|        |                          | (3a) Base value  
|        |                          | (3b) Minimize small crystals  
|        |                          | (3c) Minimize small crystals $+ 2 \, \sigma$  
|        |                          | (3d) Maximize small crystals  
|        |                          | (3e) Maximize small crystals $- 2 \, \sigma$  
| 3      | Changing estimate of IWC$_{<100}$ |  

large differences in SW CRF occur when the cloud cover is close to unity (e.g., 15 August). Although the agreement of the simulations with observations is reasonable, it is not possible to ascertain which scheme best matches the observations. This occurs due to the difficulty of comparing the averages of 7-point measurements with model simulations representing a 200-km grid box.

Variations in LW CRF are less significant, and the precipitation falling at the ground is virtually identical for all simulations. The conversion of cloud water to rainwater is assumed to only depend on cloud water content (CWC) and temperature in the Tiedtke (1993) scheme, and hence the lack of variability in precipitation is not surprising; however, distributions with larger \( r_e \) should develop precipitating ice crystals more quickly. Although there were quantitative differences for the TOGA COARE simulations, similar qualitative trends were noted as in the ARM TWP simulations. An especially noticeable feature for TOGA COARE was a time period between 30 December and 5 January when there were large differences in SW CRF with cloud covers close to unity for all simulations.

To quantify the effect of different microphysical parameterizations on the radiative budget, Table 4 lists the SW and LW CRFs averaged over the entire time period at both the surface (SFC) and TOA. Differences in averaged LW CRF, with maximum differences of 6.4 W m\(^{-2}\), are much less than differences in averaged SW CRF, with maximum differences of 34.2 W m\(^{-2}\). This maximum difference occurs between the simulation in which \( r_e \) is 2 \( \sigma \) higher than the base value, with an averaged SW CRF of 78.3 W m\(^{-2}\), and the simulation
with a constant \( r_e \) of 10 \( \mu \text{m} \), with an averaged SW CRF of 112.5 \( \text{W m}^{-2} \). For simulations corresponding to uncertainties in the \( r_e \) parameterizations developed here, the maximum difference in TOA SW CRF of 17.7 \( \text{W m}^{-2} \) occurred for simulations with \( r_e \) two standard deviations greater than and less than the mean value. Note that the differences between simulations with varying microphysics are larger than those associated with the initial perturbations in the temperature and moisture fields. Further, systematic differences between simulations occur in the expected direction, namely, an enhanced reflection is associated with smaller particles. However, due to nonlinear feedbacks, smaller \( r_e \) do not always imply larger SW CRF (where larger henceforth means more negative SW CRF), as the average SW CRF is 85.7 \( \text{W m}^{-2} \) for the simulation in which \( r_e \) is 1 \( \sigma \) lower than the base case, and 88.8 \( \text{W m}^{-2} \) for the base case. Qualitatively similar results were obtained for the TOGA COARE simulations; however, the maximum difference between SW CRFs was only 19.9 compared to 34.2 \( \text{W m}^{-2} \) for the ARM TWP simulations.

An additional test was performed to verify that the systematic differences between \( r_e \) schemes could be attributed to parameterization differences and not due to the chaotic nature of the dynamical system. For the simulation in which \( r_e \) is 2 \( \sigma \) lower than the base value, an ensemble of runs were performed with the same varying temperature and moisture perturbations used before. The mean of the SW CRF from these simulations was 94.8 \( \pm 5.1 \text{ W m}^{-2} \), similar to the mean value given in Table 4. This again shows the robustness of the derived sensitivities to microphysical parameterizations.

Figure 6 plots the temporal evolution of ice and liquid optical depths (\( \tau_i \) and \( \tau_l \)), ice and liquid water paths (IWP and LWP, respectively), and column averaged effective radii for ice and liquid clouds for the same simulations. The column-averaged effective radius (Mazin et al. 1996; McFarquhar and Heymsfield 1998) is defined as

\[
\tau_e = \frac{3\text{LWP}}{4G_i\rho_i} \quad (4)
\]

for liquid water clouds (\( r_e \)), where LWP is the vertically integrated liquid water path and \( G_i \) is the vertically integrated projected area for liquid-phase particles, and as

\[
\tau_e = \frac{\sqrt{3}\text{IWP}}{3G_i\rho_i} \quad (5)
\]

for ice-phase clouds, where IWP is the ice water path and \( G_i \) is the vertically integrated projected area for ice-phase particles. The constants are different in Eqs. (4) and (5) because the \( \tau_e \) definition for ice was originally chosen to match the Fu (1996) definition. The \( r_e \) defined by Eqs. (4) and (5) are different than the \( r_e \) that would be detected by a satellite using visible and near-infrared radiances to measure the same cloud; in that case, \( r_e \) would be an average corresponding to only the uppermost parts of clouds, which lie within the uppermost four or five optical depths of the clouds (McFarquhar and Heymsfield 1998).

There are substantial differences in \( \tau_e \) predicted by various simulations because changes in extinction optical depth at any model layer are roughly proportional to changes in \( r_e \) at that level. The \( \tau_e \) for the 10-\( \mu \text{m} \) simulation is especially high because the distributions of smaller crystals have larger cross-sectional area and larger extinction optical depth, given the same IWC as for the other simulations. Other variables, not directly affected by changes in the ice cloud parameterization, such as \( \tau_i \), LWP, and \( \tau_e \), also vary between simulations because the simulations are interactive. Therefore, variations in cloud heating rates, induced by different \( r_e \) estimates, cause different evolution of both LWC and IWC, which in turn feeds back upon the radiative heating and cooling rates. These feedbacks are significant because changes in IWP, LWP, \( \tau_i \), \( \tau_l \), and/or \( \tau_e \) can amplify or reduce the radiative forcings associated with variations in \( r_e \).

A large difference in optical properties of water or ice clouds alone may not indicate a large difference in CRF. For example, the TOA SW CRF does not differ substantially between simulations around 22 August; at this time IWP from the 10-\( \mu \text{m} \) simulation is larger than the IWP from the base simulation, but a smaller LWP compensates for this difference. In general, though, larger differences in IWP or LWP are associated with larger differences in SW CRF. Differences in cloud cover, IWP, or LWP, do not alone explain why SW CRFs vary between the different sets of simulations. Comparing Fig. 5 with Fig. 6 shows that the greatest differences in

<table>
<thead>
<tr>
<th>Case</th>
<th>SW CRF TOA (( \text{W m}^{-2} ))</th>
<th>SW CRF SFC (( \text{W m}^{-2} ))</th>
<th>LW CRF TOA (( \text{W m}^{-2} ))</th>
<th>LW CRF SFC (( \text{W m}^{-2} ))</th>
</tr>
</thead>
<tbody>
<tr>
<td>(2a) ( r_e = r_{\text{best}} )</td>
<td>-88.8</td>
<td>-95.9</td>
<td>45.6</td>
<td>139.5</td>
</tr>
<tr>
<td>(2b) ( r_e = r_{\text{best}} - 1 \sigma )</td>
<td>-85.7</td>
<td>-92.0</td>
<td>46.7</td>
<td>136.4</td>
</tr>
<tr>
<td>(2c) ( r_e = r_{\text{best}} - 2 \sigma )</td>
<td>-96.0</td>
<td>-103.1</td>
<td>50.0</td>
<td>140.5</td>
</tr>
<tr>
<td>(2d) ( r_e = r_{\text{best}} + 1 \sigma )</td>
<td>-91.9</td>
<td>-100.2</td>
<td>46.5</td>
<td>143.5</td>
</tr>
<tr>
<td>(2e) ( r_e = r_{\text{best}} + 2 \sigma )</td>
<td>-78.3</td>
<td>-84.5</td>
<td>44.3</td>
<td>137.2</td>
</tr>
<tr>
<td>(1a) ( r_e = 10 \mu\text{m} )</td>
<td>-112.5</td>
<td>-119.0</td>
<td>50.7</td>
<td>141.7</td>
</tr>
</tbody>
</table>
SW CRFs between simulations occurs when \( \tau_l \) is larger and when \( \tau_i \) is smaller; when \( \tau_l \) is large, the differences associated with variations in ice cloud schemes are reduced because liquid clouds, when present, make substantial contributions to the reflection. Reasons for differences between the simulations will be further discussed in section 4d.

Figure 7 shows SW and LW CRFs at TOA, \( \tau_l \), and \( \tau_{\text{re}} \) as a function of time for the noninteractive simulations at the ARM TWP site. Here, differences in CRFs are only associated with effects directly arising from variations in \( r_e \). Other variables, such as cloud cover, precipitation rate, LWP, \( \tau_l \), and \( r_e \), are not plotted because they are identical between simulations. Table 5 shows the average CRFs at the surface and at TOA. Differences in LW CRFs at TOA between simulations is 6.4 W m\(^{-2}\), which is similar to the differences calculated for the interactive simulations. As in Fig. 5 and Table 4, the major differences occur between the observationally based schemes and the scheme with a very low \( r_e \) of 10 \( \mu \text{m} \); differences between alternate versions of the observationally based parameterization are not as large. The maximum difference between SW CRFs between schemes is 21.7 W m\(^{-2}\), smaller than the difference of 33.2 W m\(^{-2}\) for the interactive simulations. The maximum difference between simulations with \( r_e \) two standard deviations greater than and less than the base case is only 7.0 W m\(^{-2}\), much lower than the 17.7 W m\(^{-2}\) difference for the interactive scheme. The larger differences for the noninteractive simulations shows the importance of the feedbacks of the heating rates on the cloud properties.
Figure 7. Temporal variation of (a) SW CRF at TOA, (b) LW CRF at TOA, (c) total optical depth \( \tau \), and (d) \( r_e \) for 35-day time period of noninteractive ARM TWP simulations. Different line types represent different simulations as indicated in legend. Thick solid line represents simulation with constant \( r_e \) of 10 \( \mu \)m.

Table 5. As in Table 4, except for noninteractive simulations.

<table>
<thead>
<tr>
<th>Case</th>
<th>SW CRF TOA (W m(^{-2}))</th>
<th>SW CRF SFC (W m(^{-2}))</th>
<th>LW CRF TOA (W m(^{-2}))</th>
<th>LW CRF SFC (W m(^{-2}))</th>
</tr>
</thead>
<tbody>
<tr>
<td>(2a) ( r_e = r_{\text{best}} )</td>
<td>−89.1</td>
<td>−96.4</td>
<td>45.6</td>
<td>140.0</td>
</tr>
<tr>
<td>(2b) ( r_e = r_{\text{best}} - 1 \sigma )</td>
<td>−91.1</td>
<td>−98.1</td>
<td>46.8</td>
<td>140.1</td>
</tr>
<tr>
<td>(2c) ( r_e = r_{\text{best}} - 2 \sigma )</td>
<td>−93.5</td>
<td>−100.4</td>
<td>48.2</td>
<td>140.1</td>
</tr>
<tr>
<td>(2d) ( r_e = r_{\text{best}} + 1 \sigma )</td>
<td>−87.7</td>
<td>−95.1</td>
<td>44.5</td>
<td>140.0</td>
</tr>
<tr>
<td>(2e) ( r_e = r_{\text{best}} + 2 \sigma )</td>
<td>−86.5</td>
<td>−94.0</td>
<td>43.5</td>
<td>139.9</td>
</tr>
<tr>
<td>(1a) ( r_e = 10 \mu )m</td>
<td>−108.2</td>
<td>−114.3</td>
<td>49.9</td>
<td>140.3</td>
</tr>
</tbody>
</table>

Figure 8 shows SW and LW CRFs at TOA computed for two simulations using different realizations of \( r_e \), keeping the treatment of \( r_e \) identical to the base simulation. One simulated scheme uses Bower et al.'s (1994) parameterization, which is used in the other simulations described in this paper, whereas the other assumes a constant \( r_e \) of 10 \( \mu \)m. Results from interactive and noninteractive simulations are shown for the 10-\( \mu \)m simulation; the calculated cloud water from the simulations with Bower et al. (1994) scheme is used as the basis for the noninteractive scheme. Substantial differences in SW CRFs at TOA occur between the 10-\( \mu \)m simulation and the Bower et al. (1994) simulation because given the same LWC, less solar radiation is reflected for larger \( r_e \), especially when not many ice clouds are present. The averaged SW CRFs at TOA range from −88.8 W m\(^{-2}\) using the Bower et al. (1994) \( r_e \) scheme to −78.6 W m\(^{-2}\) using the interactive version of the constant 10-\( \mu \)m scheme, to −71.8 W m\(^{-2}\) for the noninteractive scheme. There is much less variation in the LW CRFs at both the surface and at TOA; the maximum difference between LW CRFs between simulations is 2.9 at the surface and 1.3 W m\(^{-2}\) at TOA. The range of variations in CRFs associated with varying liquid cloud microphysical properties is comparable to those associated with varying ice cloud microphysical properties. Therefore, variations in the properties of liquid water clouds, produced from the differing vertical profiles of heating associated with changes of ice cloud microphysics, have additional effects on the radiative forcing of the system. Unfortunately, further discussions of the importance of varying liquid cloud properties are beyond the scope of this paper.

For both the ARM TWP and TOGA COARE ice
Simulations, there were larger differences between simulations using interactive microphysics than for simulations using noninteractive microphysics. This increased sensitivity is not a direct effect from varying $r_e$, but rather occurs because this variation in $r_e$ causes changes that feed back upon the ice and water mass content. This change in cloud water content and the associated change in radiative properties will henceforth be termed an indirect effect. This should not be confused with the typical indirect effect associated with effects on radiation from modification of cloud properties by anthropogenic pollutants.

c. Why CRFs vary between simulations

CRFs are directly affected by changes in the parameterized ice cloud properties and indirectly affected by variations in liquid and ice cloud mass, as produced from different feedbacks operating in the SCM. To better understand how these direct and indirect processes affect the CRFs, the cloud conditions under which CRFs differ most between different simulations are first identified. The results of the simulations with a constant $r_e$ of 10 $\mu$m and with $r_e$ characterized by the base conditions of Fig. 2 (simulation 2a) are used for this purpose since there are substantial differences between these simulations. The data from the ARM TWP and TOGA COARE simulations are used together for these investigations.

Figure 9 shows a scatterplot of the difference between the TOA SW CRF predicted from interactive simulations for the base parameterization and for the 10-$\mu$m simulation, plotted against the difference in effective cloud optical depth between the two simulations, $\tau_{e,\text{base}} - \tau_{e,10}$, where $\tau_{e,\text{base}}$ represents the effective optical depth from the base simulation and $\tau_{e,10}$ represents the effective optical depth from the 10-$\mu$m simulation; points corresponding to nighttime conditions have been removed. Each point represents a 1-h average. Effective optical depth is calculated using subgrid columns following Jacob and Klein (1999), hence, it is the vertical integral of extinction coefficient multiplied by cloud coverage at each level, and provides information about the optical density of a SCM grid box. The solid line represents a best fit to the data, and a Pearson’s correlation coefficient of 0.48 indicates that, despite the scatter, there is at least a trend to greater differences in SW TOA CRFs as differences between $r_e$ increase for the two cases. No other quantity was found that gave as good as correlation coefficient when plotted against the differences in CRFs.

Two dashed lines are plotted in Fig. 9. Points lying between the dashed lines correspond to points where the difference in CRF is principally associated with dif-
Fig. 9. Difference in CRF between base simulation [Table 3, series 2, simulation (a)] and simulation with constant \( r_e \) of 10 \( \mu \)m [Table 3, series 1, simulation (a)], as function of difference between effective optical depth for same two simulations. Results from interactive simulations plotted for both TOGA COARE (dots) and ARM TWP (pluses) domains. Solid line is best fit to data with regression coefficient of \(-0.48\); dashed lines represent \( \pm 50\% \) slope of solid line.

Differences in \( \tau_e \). When examining points that fall below the lower dashed line, and including only points for which \( \tau_e,\text{base} - \tau_e,10 < -1.0 \), the mean effective liquid optical depth from the base simulation, \( \tau_e,\text{base} \), is \( 9.8 \pm 7.5 \), which is much larger than \( \tau_e,\text{base} \) for points falling above the higher dashed line, given by \( 3.7 \pm 3.7 \). The difference is statistically significant. The patterns are even more clear when results from noninteractive simulations are plotted (figures not shown), with \( \tau_e,\text{base} \) being \( 12.5 \pm 6.9 \) for points above an equivalent dashed line and \( \tau_e,\text{base} \) \( 3.4 \pm 3.3 \) for points below an equivalent dashed line. Hence, the effective optical depth of liquid clouds has a major impact on how much CRFs vary between simulations with varying ice cloud properties.

Comparing ice cloud microphysical properties for the same two populations, yields little difference. For example, for the base simulation, the mean cloud-averaged effective radius for ice clouds is \( 33.4 \pm 10.7 \) for points below the dashed line and \( 31.2 \pm 7.3 \) \( \mu \)m for points above the dashed line; liquid water cloud averaged effective radii are \( 6.3 \pm 1.4 \) and \( 6.1 \pm 2.0 \) \( \mu \)m for the same two populations, hardly a significant difference. For the base case, visible asymmetry parameters averaged over the depth of a cloud range from \( 0.790 \pm 0.015 \) for points under the lower dashed line to \( 0.788 \pm 0.014 \) for points above the higher dashed line. Other single-scattering properties also show negligible differences between populations and hence do not have a large direct impact on the CRFs.

This does not indicate that single-scattering properties are not important. They do affect the prediction of LWC and IWC through their effects on the heating rate profiles. This is the previously mentioned indirect effect, which can amplify the direct effect of varying microphysical properties. For example, from Table 5, it is seen that increasing the \( r_e \) by two \( \sigma \) leads to a reduction in reflection at the TOA leading to a 2.6 W m\(^{-2}\) change in SW CRF at the TOA and of 2.4 W m\(^{-2}\) at the surface from direct effects (noninteractive simulation). However, for the interactive simulations shown in Table 4, the reduction in reflection leads to a change of 10.5 W m\(^{-2}\) in SW CRF at TOA and of 11.4 W m\(^{-2}\) at the surface. Indirect effects can also reduce the impact predicted from the noninteractive simulations. For example, reducing \( r_e \) by 1 \( \sigma \) from the base case increases reflection of shortwave radiation, changing SW CRF at TOA by 2.0 W m\(^{-2}\) for noninteractive simulations. However, there is actually a reduction in SW CRF at TOA by 2.9 W m\(^{-2}\) for the interactive simulations.

For the development of improved representations of ice cloud microphysics, these feedbacks on the amount of liquid and ice mass content must be understood. Hence, it is necessary to examine how different microphysical parameterizations affect the heating profiles.
within clouds, and hence the prognostic equations for the amount of cloud water/ice. The same two simulations are used in this investigation.

d. Vertical profiles of cloud properties and heating rates

Figure 10 shows the vertical profiles of CWC, \( r_e \), cloud fraction and cloud extinction as a function of height for the base parameterization, and for the 10-\( \mu \)m simulation for the interactive and noninteractive ARM TWP simulations averaged over the whole time period. Two lines are plotted for \( r_e \), corresponding to the effective radius of liquid and ice particles, respectively, with the overlap region representing mixed-phase clouds.

The major difference between the base simulation and the 10-\( \mu \)m simulation is the vertical profile of extinction and \( r_e \) for ice clouds; the extinction due to upper clouds is substantially less for the base simulation. This is a direct effect of altering the microphysical parameterization. However, substantial differences in LWCs exist when the interactive simulations are compared. The base simulation has substantially higher LWCs around 825 hPa and substantially lower LWCs around 750 hPa when compared to the interactive 10-\( \mu \)m simulation; this is also seen in the vertical profiles of extinction from liquid water clouds at the same pressure levels. The reasons for these differences need to be investigated in the context of the various terms in the prognostic equation for cloud water content.

The Tiedtke (1993) prognostic scheme is used to define the time evolution of cloud water content and fractional cloud cover. The time change of the grid-averaged cloud water/ice content is given by

\[
\frac{dq_c}{dt} = A(q_c) + S_{CV} + S_{NL} + C - E - G_P - \frac{1}{\rho} \frac{\partial}{\partial z} (\rho w' q_e')_{entr},
\]

where \( A(q_c) \) represents transports of cloud water \( q_c \) through the boundaries of the grid volume, \( C \) is the condensation/sublimation rate, \( E \) is the rate of evaporation, \( G_P \) is the rate of generation of precipitation by autoconversion, \( S_{CV} \) and \( S_{NL} \) are sources of cloud water/ice from convection and boundary layer turbulence, and the last term is the flux divergence due to entrainment processes at the top of stratocumulus clouds. In order for the differences in Fig. 10 to occur, some of the terms in Eq. (6) must vary depending upon the microphysical parameterization used.

Figure 11 compares the terms in Eq. (6), averaged over the length of the simulation, for both the noninteractive (top panels) and interactive (bottom panels) base simulation and 10-\( \mu \)m simulation for the ARM
TWP domain. Analysis for the TOGA COARE domain yielded similar qualitative conclusions. The values of the terms in Eq. (6) are plotted in the left panels, and the difference of terms between the base simulation and the 10-μm simulation is plotted in the right panels. The addition of cloud water from convection ($S_{CV}$) and the loss of cloud water from autoconversion to rain ($G_P$) dominate the moisture budget. However, for the noninteractive simulations, these terms are identical and differences in the moisture budget occur due to differences in the rate of evaporation and in the rate of condensation and sublimation; it is hence these terms that are ultimately causing the variation of CWC between simulations and hence the indirect effect. The differences between $S_{CV}$ and $G_P$ dominate the difference in moisture budget for the interactive simulations, and note that the magnitude of differences in the moisture budget is much larger for the interactive simulations than for the noninteractive simulations. Further, for the interactive simulations, the difference in the moisture budget oscillates between positive and negative values many times with increasing altitude, whereas the signal is much more clear for the noninteractive simulations; at levels below 525 hPa the base simulation gains con-
densed water at a faster rate than the 10-μm simulation, but at levels above 525 hPa the opposite is true.

The differences between E and C (COND), which ultimately cause the differences between the simulations, occur because of the discrepancy in heating rates produced between the base simulation and the 10-μm simulation. The vertical profiles of heating rates are shown in Fig. 12 for the ARM TWP simulations. The left panel represents the noninteractive simulations whereas the right panel represents the interactive simulations. The majority of the difference in the heating rates between the base (thick lines) and 10-μm simulations (thin lines) occurs due to infrared cooling. It is easiest to examine results for the noninteractive simulations because differences in CWC dominate the interactive simulations, and further there are oscillations in the difference with altitude for the interactive simulations. There is less cooling near cloud tops around 250 hPa for the base simulation, as compared to the 10-μm simulation, whereas there is more cooling for the base simulation at lower levels in the ice clouds between 400 and 500 hPa. These differences occur because the infrared optical depth, which is closely related to the solar extinction optical depth, is larger for the 10-μm simulations than it is for the base simulation. Hence, between 400 and 500 hPa there is more cooling because of the larger infrared extinction optical depths. At 250 hPa, less cooling occurs for the 10-μm simulation probably because of a reduction in the infrared radiative flux reaching this level. At this level, the smaller crystals in the 10-μm simulation would also be causing an enhancement of solar reflection.

This analysis just starts to explain the causes for differences between simulations. A subsequent study, where impacts associated with use of different solar and infrared radiative transfer schemes will further examine these issues.

e. Other sensitivity studies

Another sensitivity study examined the impact of randomly choosing parameterization coefficients in Eq. (2) at each model time step. Such a study probably represents natural cloud processes better than using a mean parameterization because the scatter of the data in Fig. 2 is not represented by set coefficient values. Although \( r_\text{e} \) generated in this way may have sudden temporal jumps, it should be noted that substantial microphysical evolution can occur during the 1-h time step used for calling the shortwave routines. However, because of the large variations, the simulations probably represent an upper bound for the effects of \( r_\text{e} \) variations on CRF. Until reasons for the variability are better understood and parameterized, the approach presented here is the
The parameterization was implemented in the Scripps SCM, and conditions observed at the TOGA COARE and ARM TWP sites were simulated. Sensitivity studies determined how uncertainties in the parameterization scheme scaled up to predicted uncertainties in cloud radiative forcing (CRF). The mechanisms by which different parameterization, impact CRF were examined by comparing a simulation of both the base parameterization, where the mean $r_s$ from the size and shape distributions was written as a function of IWC, and a parameterization assuming a constant $r_s$ of 10 $\mu$m. Both
interactive simulations, where changes in heating rates associated with different microphysical parameterizations feed back upon the predicted cloud water content, and noninteractive simulations, where such feedbacks are not allowed, were used in this study.

The principal findings of this study are summarized below:

1) Current parameterizations of \( r_e \) for large-scale models do not properly account for variations in \( r_e \) that cannot be represented by a simple equation. For example, within two standard deviations of the mean, \( r_e \) can range from 16 to 24 \( \mu \)m for an IWC of 0.01 g m\(^{-3}\) and from 24 to 43 \( \mu \)m for an IWC of 0.1 g m\(^{-3}\). Until information about reasons for such variations is known, or until multivariate dependences of \( r_e \) can be described better, parameterizations should provide ranges of fit coefficients or ranges of possible \( r_e \) values.

2) Observational uncertainties in the measurements of small ice crystals, with diameters smaller than 100 \( \mu \)m, cause large uncertainties in the \( r_e \) parameterizations. For the widest possible range of assumptions, which most likely overestimates uncertainty, the most likely \( r_e \) can vary from 12 to 18 \( \mu \)m for an IWC of 0.01 g m\(^{-3}\) and from 21 to 30 \( \mu \)m for an IWC of 0.1 g m\(^{-3}\).

3) Simulations conducted by randomly choosing \( r_e \) at each time step within one or two standard deviations of the mean parameterized value, show that the TOA SW CRF can vary by up to 13.9 W m\(^{-2}\) from that value predicted using the parameterization of mean \( r_e \); differences in longwave CRF are substantially less. Further, these random simulations typically lead to an enhancement of shortwave reflection by up to 4.9 W m\(^{-2}\), suggesting that a simulation based on an average parameterization does not give the same result as the average of a series of parameterizations.

4) Simulations conducted that account for observational uncertainties and the variances of \( r_e \) from the mean values of those parameterizations show that there can be uncertainties in the shortwave CRF of approximately 25 W m\(^{-2}\) on average.

5) Differences in microphysical parameterizations of liquid water clouds produce variations in predicted CRF of up to 17 W m\(^{-2}\), values that are just as large as those associated with changes in the microphysical parameterization of ice clouds.

6) Differences in longwave heating rates, predicted by different microphysical parameterizations, feed back upon the cloud water content predicted by the model. This change in cloud water content, compared to simulations using other parameterizations, affects the CRF in a way that either amplifies or reduces the change in CRF that is directly associated with a modification of the cloud microphysical properties (i.e., smaller \( r_e \) producing an enhancement of shortwave reflection).

7) The model-calculated CRF is most strongly correlated with the effective cloud optical depth, which is defined as the vertical integral of extinction coefficient multiplied by cloud cover. However, there is considerable variation in CRF not explained by effective cloud optical depth, which is associated with variations in liquid cloud and ice cloud total optical depth.

8) Simulations verified that the derived sensitivities to microphysics were a consequence of parameterization differences and not a consequence of the chaotic nature of the simulated system.

Future work should concentrate on determining how representative the parameterization developed here is, in order to determine whether it can be extended to other cloud types and clouds occurring in other geographic regimes. Further, if multivariate relations for \( r_e \) as functions of other prognostic variables can be determined, then the random variability included in this parameterization could be limited. Additionally, attempts should be made to further characterize the large variation in \( r_e \) that cannot be parameterized as a simple function of IWC. Modeling studies need to concentrate on further defining the details of the interactions between cloud, dynamical, and radiative properties. Future studies will concentrate on how radiative parameterizations affect the vertical profiles of heating within clouds, and hence on the predicted cloud amount.

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APPENDIX

Rederivation of Ebert and Curry (1992) Parameterization

Assuming that ice crystals could be approximated by polydispersed randomly oriented hexagonal columns, EC92 used the single-scattering properties computed by Takano and Liou (1989) for four crystal distributions and five spectral intervals to develop a parameterization for the shortwave optical properties of ice clouds in terms of an effective radius. This parameterization cannot be directly applied to simulations where effective radius is computed following Fu’s (1996) definition as
EC92 stated that their effective radius corresponds to spheres of equal surface area. Hence, an alternative form of the EC92 parameterization is derived, using the geometries of the hexagonal columns given by EC92 combined with the size distributions given in Takano and Liou’s (1989) Fig. 2 to calculate $r_e$ following Fu’s (1996) definition. The single-scattering properties are given in Takano and Liou’s (1989) Table 2. Because most real ice clouds are not composed entirely of hexagonal columns, this rederived parameterization may be more appropriate for use in large-scale models because the calculated radiative properties of particles, which conserve both volume and projected area more accurately, resemble the radiative properties of actual particles than those that conserve only volume or area.

When regressions are fit to the resulting data, the new parameterizations can be expressed as

$$\tau_\lambda = IWP(a_i + b_i r_e), \quad (A1)$$

$$1 - \omega_i = c_i + d_i r_e, \quad (A2)$$

$$g_i = e_i + f_i r_e, \quad (A3)$$

where $a_i$ to $f_i$ are the constants given in Table A1 and $i$ is the spectral interval. Note that the third and fourth spectral moment are combined into a single band, weighted according to the fraction of incident solar radiation at the top of the atmosphere, for use in the Scripps SCM.

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