Tests and improvements of GCM cloud parameterizations using the CCCMA SCM with the SHEBA data set

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Abstract

A GCM cloud microphysics parameterization is tested and improved using the CCCMA single-column model with cloud properties obtained at the Surface Heat Budget of the Arctic Ocean experiment (SHEBA) during the period of November 1997 to September 1998. The ECMWF reanalysis water vapor profile is scaled with rawinsonde data so that the new relative humidity profiles are compatible with rawinsonde data for nudging purposes. This study demonstrates that the treatment of ice nucleation number concentration is the controlling factor of the overestimation of monthly mean ice water path originally produced by this model. The parameterizations of accretion processes are modified to consider the accumulation due to an increase of precipitation flux through a model layer related to accretion processes. The horizontal inhomogeneity effect of cloud liquid water is considered in parameterization of autoconversion process. A new method developed for mixed-phase clouds to determine the water vapor saturation and partitioning of the condensed water into different phases is also tested in this model.

When using a nudging technique with the adjusted ECMWF water vapor profile the model can well simulate the monthly total cloud cover and daily precipitation rate for the SHEBA period. Using the modified cloud microphysics parameterizations including improved treatments for accretion processes, ice nucleation number concentration, and auto-conversion, the monthly mean cloud liquid water path and ice water path are suitably simulated and compare reasonably well to those derived from measurements.

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1. Introduction

Clouds cover about 60% of the Earth’s surface and play an important role in regulating the Earth’s radiation budget. In current climate modeling, the lack of understanding of cloud is still a major uncertainty (Houghton et al., 1996). Inter-comparison studies of general circulation model (GCM) simulations (e.g., Randall et al., 1998) indicate that different models simulating polar processes show large discrepancies in the Arctic. Curry and Ebert (1992) and Zhang et al. (1996) have demonstrated the importance of specific cloud macro- and micro-physical properties, including cloud amount, cloud base height, cloud phase, particle size and shape, and cloud ice/water contents, on cloud-radiation and ice-albedo feedback mechanisms. The cloud-radiation feedback (CRF) in the Arctic significantly influences the way heat passes through the Arctic system. Because of the complexity and importance of
polar cloud radiative effects, it is necessary to gain an insight into them through a combination of modeling and observational studies.

The difficulties associated with simulating cloud radiative effects in GCM studies exist because of the currently inadequate understanding of cloud processes including the related dynamic, thermodynamic and microphysics processes. The microphysics processes are particularly important because the factors determining cloud optical properties are directly related to these processes. It is crucial to improve parameterizations of microphysics processes in GCMs to ensure reasonable atmospheric optical parameters for the simulation of radiative energy budget.

Due to the complexity of GCMs, it is difficult to isolate specific processes and study them in GCM simulations. The single-column model (SCM) has been promoted as a useful testbed for cloud parameterizations (Randall et al., 1996), but providing suitable boundary conditions to SCM is extremely challenging (Zhang and Lin, 1997; Mace and Ackerman, 1996; Randall et al., 1996).

The Surface Heat Budget of the Arctic Ocean (SHEBA) project is motivated by the large discrepancies among simulations by global climate models of the present and future climate in the Arctic and by uncertainty about the impact of the Arctic on climate change (Moritz et al., 1996). The period of the SHEBA experiments is from 1997 to 1999 at the North Pole SHEBA ice station, which include rawinsonde, lidar, radar, meteorological surface and a microwave radiometer observations, etc. Accompanied by ECMWF provided hourly column output of the water vapor and temperature forcing data, this integrated observation data set is well suited for testing GCM cloud parameterizations through SCM simulations in the Arctic region.

In this study, we applied a recent version of the Canadian Centre for Climate Modeling and Analysis (CCCMA) single-column model (CSCM) (Lohmann et al., 1999) to the SHEBA year to test and improve GCM cloud parameterization in the Arctic region. The CSCM annual cycle simulation is carried out using the ECMWF forcing (Beesley et al., 2000) with a nudging technique. We describe this model and the data used along with nudging techniques in Section 2. In Section 3, we present the problem in nudging using ECMWF reanalysis water vapor profile and discuss our modification of the data to alleviate this problem. The test and improvement of cloud microphysics parameterization using SHEBA data are shown in Section 4. We discuss the effect of a new partitioning method for water vapor in mixed-phase clouds, as derived from in-situ measurements in Section 5. The conclusions are given in Section 6.

2. Descriptions of model and data and nudging technique

2.1. Model description

The CCCMA single-column model (CSCM) used in this study is adapted from the second-generation CCCMA GCM (McFarlane et al., 1993). It predicts horizontal wind components, temperature, water vapor and total condensed water. The turbulence scheme contains a prognostic equation for the turbulent kinetic energy (TKE) (Abdella and McFarlane, 1997). Other second-order quantities are determined diagnostically through a parameterization of the third-order moments based on a convective mass-flux argument. Cumulus clouds are represented by a bulk model including the effects of entrainment and detrainment on the updraft and downdraft convective mass fluxes (Zhang and McFarlane, 1995). The radiation code is based on two-stream solutions of the radiative transfer equation with six spectral intervals in the infrared spectrum (Morcrette, 1989) and two in the solar spectrum (Fouquart and Bonnel, 1980). Gaseous absorption due to water vapor, CO₂, O₃, CH₄, N₂O, and CFCs is included.

Two kinds of cloud schemes are available as options in the CSCM. One is an explicit cloud scheme; the other is a statistical cloud scheme. The explicit cloud scheme is used in this study, which is described in detail by Lohmann and Roeckner (1996). It has prognostic variables for liquid water content (qₗ) and ice water content (qᵢ) and uses an explicit approach for condensation and cloud cover based on Sundqvist (1978). In explicit cloud scheme, cloud fraction (A) is a diagnostic function of relative humidity (Sundqvist et al., 1989).

\[
A = 1 - \sqrt{1 - A₀} \tag{1}
\]

\[
A₀ = (Rh - Rh₀)/(1 - Rh₀) \tag{2}
\]

\[
Rh₀ = Rh_{top} + (Rh_{sfc} - Rh_{top}) \exp \left[ -\frac{(P_{sfc} - p)}{p} \right] \tag{3}
\]

where \( p_{sfc} \) and \( p \) are the air pressure at surface and in atmosphere, respectively. Rh is the grid-mean relative humidity; \( Rh₀ \) is a threshold specified as a function of height based on the work of Xu and Krueger (1991). It decreases from 0.95 near the surface to 0.6 at top of the atmosphere.
Condensation only occurs in the cloudy part of the grid box if moisture convergence due to advection/turbulence/adiabatic cooling occurs. The grid mean condensation rate $Q_{\text{cond}}$ is

$$Q_{\text{cond}} = A \cdot \left[ \text{ATC}(q_v) - \frac{\partial q_{\text{sat}}}{\partial t} \right]$$

where $\text{ATC}(q_v)$ is the growth of grid mean water vapor mixing ratio caused by the moisture convergence due to advection or turbulence, $q_{\text{sat}}$ is the water vapor saturation mixing ratio, and $q_v$ is the grid mean water vapor mixing ratio.

The implementation of the statistical cloud scheme is described in detail by Lohmann and Roeckner (1996). The microphysics processes are the same for these two schemes. According to Lohmann and Roeckner (1996), the prognostic equations include

$$\frac{\partial q_v}{\partial t} = \text{ATC}(q_v) - A \left( Q_{\text{cond}}^c + Q_{\text{dep}}^c \right) + (1-A) \left( Q_{\text{evp}}^c + Q_{\text{sub}}^c - Q_{\text{cond}}^c - Q_{\text{dep}}^c \right)$$

$$\frac{\partial q_i}{\partial t} = \text{ATC}(q_i) + A \left( Q_{\text{cond}}^i - Q_{\text{aut}}^i - Q_{\text{rcl}}^i - Q_{\text{sac}}^i \right) - Q_{\text{fr}}^i - Q_{\text{frs}}^i - Q_{\text{frc}}^i + (1-A) Q_{\text{cdn}}^i$$

The superscripts (c) and (o) refer to the cloudy and cloud-free part of the grid box. The microphysical processes parameterized in the CSCM are condensational (depositional) growth of cloud droplets (ice crystals), $Q_{\text{cond}}^c$ ($Q_{\text{dep}}^c$); homogeneous ($Q_{\text{fr}}^c$), heterogeneous ($Q_{\text{frs}}^c$), and contact ($Q_{\text{frc}}^c$) freezings of cloud droplets; autoconversion (aggregation) of cloud droplets (ice crystals), $Q_{\text{aut}}^c$ ($Q_{\text{rcl}}^c$); accretion of cloud droplets ($Q_{\text{sac}}^c$) and cloud ice ($Q_{\text{sac}}^c$) by snow and of cloud droplets by rain ($Q_{\text{rcl}}^c$); evaporation/sublimation of cloud liquid water and rain (cloud ice and snow), $-Q_{\text{evp}}^c$, $-Q_{\text{sub}}^c$; and melting of cloud ice, $Q_{\text{mlt}}^i$. The precipitation formation rates are based on Levkov et al. (1992) that include the autoconversion rate for warm clouds derived from the stochastic collection equation (Beheng, 1994) and aggregation rate for cold clouds based on Murakami (1990). $q_v$, $q_i$ and $q_i$ are grid mean mass mixing ratio of water vapor, cloud liquid water content and cloud ice water content in kg/kg.

The CSCM also includes prognostic equations for the number concentrations of cloud droplets, $N_i$, and ice crystals, $N_i$ with unit of $(1/m^3)$, following Levkov et al. (1992) and Lohmann et al. (1999):

$$\frac{\partial N_i}{\partial t} = \frac{N_i}{q_i} \left( \frac{Q_{\text{aut}}^c + Q_{\text{rcl}}^c}{q_i} \right) - \frac{N_i}{q_i} \left( Q_{\text{fr}}^c + Q_{\text{frs}}^c + Q_{\text{frc}}^c \right) - Q_{\text{nself}} + \text{ATC}(N_i)$$

The full description of the microphysics parameterizations in Eqs. (5)–(9) is given by Lohmann and Roeckner (1996) and Lohmann et al. (1999).

### 2.2. Data description

The data needed to drive the CSCM are large-scale forcing data and surface observations. Also to test the model’s ability to predict properties of clouds based on a realistic atmospheric state we use the nudging technique for horizontal velocities, temperature and water vapor profiles toward the profiles obtained from objective analysis of observed data.

The location of the simulated column is in the Arctic. Simulated values of the prognostic variables correspond to averages over a horizontal area of approximately 60 km × 60 km located at the latitude of 76.373N and the longitude of 166.994W. The simulated period is from November 1997 to September 1998.

The forcing data is derived from ECMWF reanalysis hourly output including the total adiabatic tendency profiles of temperature and water vapor. The ECMWF reanalysis hourly output of surface temperature and humidity and atmosphere profiles of horizontal velocities, temperature and water vapor are used for nudging.

The observational data we use to validate model predictions for cloud cover, liquid water path and ice water path are provided by Shupe et al. (2001) based on radar observation, microwave radiometer retrieving, and radar-Doppler radar estimation, respectively. The precipitation data are provided by Moritz (personal
communication 2001) based on a nitrogen shielded snow gauge system. We also used the SHEBA rawinsonde data provided by de Roode (personal communication 2001).

2.3. Nudging

The nudging technique we used in the CSCM is based on Newtonian relaxation (Jeuken et al., 1996). We relax the model predicted horizontal velocities toward ECMWF reanalysis data based on fixed relaxation time; and relax temperature and water vapor toward ECMWF data based on the relaxation time determined from mean horizontal velocities, as follows

\[
\begin{align*}
\frac{\partial \vec{V}}{\partial t} &= T_{E_V} + \frac{\vec{V}_{\text{obs}} - \vec{V}_{\text{CSCM}}}{\tau_0} \\
\frac{\partial T}{\partial t} &= T_{E_T} + \frac{T_{\text{obs}} - T_{\text{CSCM}}}{\tau} \\
\frac{\partial q_V}{\partial t} &= T_{E_q} + \frac{q_{V\text{obs}} - q_{V\text{CSCM}}}{\tau} \\
\tau &= L_{nd} / |\vec{V}|
\end{align*}
\]

where $|\vec{V}|$ is the horizontal wind speed, $\tau_0$ is a typical time scale, $L_{nd}$ (250km) is a typical length scale. $T_{E x}$ is the tendency of variable $x$. The subscripts (obs and CSCM) refer to the observed and model simulated values for those variables.

3. Nudging using ECMWF reanalysis H2O profile with modification

The CSCM annual cycle simulations are first carried out using the explicit cloud scheme and the ECMWF forcing (Beesley et al., 2000) with a nudging technique. The simulated period is from November 1997 to September 1998.

Fig. 1 shows that the simulated monthly mean total cloud cover (TCC) is much lower than the radar observations. The simulated monthly mean daily precipitation rate (PREP) is too low compared to the SHEBA surface observations. In contrast, the simulated monthly mean liquid water path (LWP) is of the same magnitude or larger than observed and the monthly mean ice water path (IWP) is systematically larger than observed (Shupe et al., 2001).

Since microphysics processes (condensation/deposition, autoconversion/aggregation, accretions, etc.) are dependent upon cloud fraction and/or in-cloud water

![Fig. 1. Comparisons of monthly mean Total Cloud Cover (TCC), Daily Precipitation (PREP), Liquid Water Path (LWP) and Ice Water Path (IWP) between CSCM simulations and observations at SHEBA site.](image-url)
contents. Microphysics parameterizations can not be well evaluated by comparing observed and predicted precipitation and cloud water predictions based on the predicted cloud cover that is much lower than observed. Therefore, our first focus was to attempt to improve the prediction of the total cloud for the SHEBA year.

Typically, SCMs with explicit cloud schemes have two basic types of approaches to predict cloud cover and parameterize microphysics processes in cloud schemes (Fowler et al., 1996). One approach starts from microphysics processes and predicts cloud coverage in the model layer based on the presence of cloud water. This type of model cannot predict partial cloudiness. The other approach predicts cloud fraction first within each layer and then parameterizes those microphysics processes for given cloud fraction. Some previous works (Slingo, 1980, 1987; Xu and Randall, 1996) show that most clouds are subgrid-scale and fractional cloud cover must be considered, even for mesoscale models. Slingo (1980), Sundqvist (1978), Smith (1990) and Xu and Randall (1996) developed different parameterizations for predicting fractional cloud cover in large-scale models. All of them use the grid mean variable relative humidity (RH) to parameterize fractional cloud cover. In the CSCM, the Sundqvist (1978) parameterization is chosen for the explicit scheme.

An obvious possibility for underprediction of the total cloud cover is that the parameterization, which was developed for middle latitude or tropic region simulations, is not suitable in the Arctic Region. However, because we used nudging based on ECMWF profiles for temperature and water vapor mixing ratio, underprediction of the cloud cover could also be due to the humidity profiles used for nudging being dryer than the observed atmosphere.

Due to the insufficient measuring frequency of rawinsonde data, the nudging used in the CSCM simulations is based on ECMWF reanalysis temperature and water vapor profiles. Since these are a blend of observations and short-range forecast values resulting from the data assimilation process, a possible problem is that they may have biases associated with this assimilation process. Such a bias is revealed in Fig. 2 which compares monthly mean vertical integrated water vapor path between rawinsonde data and ECMWF reanalysis data.

Fig. 2 shows that the ECMWF reanalysis underestimates the water vapor path systematically during the SHEBA year. This bias may be related to the use of the following temperature-dependence partitioning method to determine the water vapor saturation mixing ratio in stratiform clouds (Tiedtke, 1993):

\[
Q_{\text{sat}} = RQ_{\text{satw}} + (1-R)Q_{\text{sati}}
\]

\[
R = \begin{cases} 
0 & T < 250.16 \text{K} \\
\left[ \frac{250.16}{T-250.16} \right]^{2} & 250.16 \text{K} \leq T \leq 273.16 \text{K} \\
1 & T > 273.16 \text{K} 
\end{cases}
\]

where \(Q_{\text{sat}}, Q_{\text{satw}}\) and \(Q_{\text{sati}}\) are water vapor saturation mixing ratio, water vapor saturation mixing ratio with respect to liquid water and ice, respectively. On the other hand, in the CSCM \(Q_{\text{sat}}\) is set to \(Q_{\text{satw}}\) or \(Q_{\text{sati}}\) when the temperature is higher than 273.16 K or lower than 235.16 K, respectively. For temperature values between 273.16 K and 235.16 K \(Q_{\text{sat}}\) is chosen to be \(Q_{\text{satw}}\) or \(Q_{\text{sati}}\) when ice water mixing ratio is less or more than \(10^{-3}\) kg/kg, respectively.

In low-temperature regimes, typical of Arctic conditions using the ECMWF method could constrain vapor mixing ratio values to be no larger than the saturation water vapor mixing ratio with respect to ice, which is frequently too dry. Additionally, the comparisons of in cloud water vapor saturation mixing ratio between aircraft data and ECMWF formula (Fu and Hollars, 2004) reveal that using this formula in such circumstances leads to a significant underestimation of the water vapor saturation mixing ratio. Thus, too much water vapor would be removed from the atmosphere to be converted to clouds.

Because the rawinsonde measurements usually have one measurement per 6 (occasionally) or 12h, they cannot be used directly to nudge the model simulations. In addition, the model predicted cloud is based on the relative humidity but not the absolute value of water vapor mass. In view of these factors, we have developed a scheme to scale the ECMWF water vapor profile as outlined below while keeping the ECMWF temperature profile unchanged:

- Calculate the relative humidity with respect to liquid water based on ECMWF reanalysis data (RH_{wecm}) and rawinsonde measurements (RH_{wraw}) separately and determine the ratio \(r = RH_{\text{wraw}}/RH_{\text{wecm}}\) for each level at time which rawinsonde measurement is available;
- Linearly interpolate the ratio \(r\) to those times when rawinsonde data is not available;
- Use those ratios to scale the ECMWF water vapor mixing ratio at each time and each level.
This procedure provides a modified set of profiles that have the same temperature profile as before but a new water vapor profile, which has a relative humidity profile that is compatible with rawinsonde data.

The new simulations based on modified ECMWF water vapor profile shown in Fig. 3 indicate that the simulated monthly mean total cloud cover agrees well with radar observations. The simulated monthly mean daily precipitation is also compared reasonably well to surface measurements. Thus, the modified profile is consistent with the physical components of the moisture and thermal forcing based on ECMWF data with nudging. Therefore, we are able to evaluate the microphysics processes with well-simulated total cloud cover and surface precipitation.

![Graph showing water vapor path comparison between rawinsonde and ECMWF](image1)

Fig. 2. Comparison of column integrated water vapor path during SHEBA year between rawinsonde measurements and ECMWF reanalysis results.

![Graph showing comparisons of TCC, PREP, LWP and IWP](image2)

Fig. 3. Comparisons of TCC, PREP, LWP and IWP between CSCM simulations using original and modified water vapor profiles for nudging, and those from observations.
Cloud fractions for December 1997 and July 1998, respectively, are shown in Figs. 4 and 5. Compared with radar observations, it is apparent that for December 1997 the model was unable to predict the presence of low clouds when using the original water vapor profile. However, using the modified data
the CSCM allowed low clouds to be simulated, especially from December 17th to December 30th. Sensitivity of the cloud cover to the water vapor profile was not as pronounced in the summer (July 1998).

However, Fig. 3 shows that the simulated cloud water paths (LWP and IWP) are much larger than the values derived from measurements. In the model, both liquid and frozen precipitation (rain and snow) are formed by conversion from cloud water, and the amounts of cloud water are always much smaller than the total time integrated condensational (depositional) water and precipitation. Usually, these microphysical processes are parameterized in terms of the initiation and growth of precipitation as nonlinear functions of cloud water content. Mass conservation implies that the total time integrated condensational plus deposition are equal to the precipitation if the evaporation (sublimation) of rain (snow) and the temporal variation of cloud water in the atmosphere are neglected. In the Arctic region, these components are much smaller than the precipitation. Thus, statistically the mean cloud water in the atmosphere presents the equilibrium state at which the time integrated condensational/depositional water and precipitation. These parameterizations were originally developed for cloud resolving model simulations but some of them may not be suitable in the circumstances under consideration here. In the following, we will examine key aspects of these parameterizations beginning with accretion processes.

4. Testing and improving microphysics parameterizations

The GCM cloud microphysics parameterizations tested in this SCM, according to Levkov et al. (1992), Lohmann and Roeckner (1996) and Lohmann et al. (1999), are based on Beheng (1994) and Lin et al. (1983) for the precipitation processes (autoconversion, accretion and aggregation, etc.). These parameterizations were originally developed for cloud resolving model simulations but some of them may not be suitable in the circumstances under consideration here. In the following, we will examine key aspects of these parameterizations beginning with accretion processes.

4.1. Accretion

According to Lohmann and Roeckner (1996), the three accretion processes in CSCM are parameterized following Beheng (1994) and Lin et al. (1983) in the forms:

\[ Q_{\text{racl}}^c = 6 \rho q_\text{cl} \frac{q_{\text{cl}}}{\Delta t} \]

\[ Q_{\text{saci}}^c = 0.1 \frac{\pi \times 3 \times 10^6 \times 4.83 \times q_\text{cl} \Gamma(3.25) \left( \frac{\rho_0}{\rho} \right)^{0.5}}{4 \times \lambda_s^{3.25}} \]

\[ Q_{\text{aci}}^c = \frac{\pi \exp[0.025 \times (T-T_0)] \times 3 \times 10^6 \times 4.83 \times q_\text{cl} \Gamma(3.25)}{4 \times \lambda_s^{3.25}} \times \left( \frac{\rho_0}{\rho} \right)^{0.5} \]

where \( \lambda_s = \left( \frac{\pi \times \rho_l \times 3 \times 10^6}{\rho_0} \right)^{0.25} \), \( q_\text{cl} \) and \( q_\text{ci} \) are the in-cloud liquid water and ice water mixing ratios, respectively; \( q_r \) and \( q_s \) are rain water and snow mixing ratios, respectively; \( \rho \), \( \rho_0 \), \( \rho_l \) and \( \rho_i \) are the densities of air, air at surface (1.3 kg/m\(^3\)), cloud ice (500 kg/m\(^3\)) and cloud water (1000 kg/m\(^3\)), respectively.

In the CSCM, the accretion processes are implemented based on a “pass through” assumption, which assumes that all precipitation contributions from each layer can reach the surface within one time step (15 min in this study). This assumption is retained here. It is acceptable for rain but may over estimate the precipitation of snow.

In the original scheme, the precipitation mixing ratios are derived from the precipitation fluxes through the relations:

\[ q_r = \frac{1}{\rho} \frac{F_r}{\Delta z/\Delta t} \]

\[ q_s = \frac{1}{\rho} \frac{F_s}{\Delta z/\Delta t} \]

where \( F_s \) and \( F_r \) are the precipitation fluxes for snow and rain, respectively, calculated based on the “pass through” assumption; \( \Delta z \) and \( \Delta t \) are the model layer thickness and time step, respectively. These treatments are of dubious validity and obviously have an unphysical dependence on the vertical resolution and time step. In effect, changing the time step or the vertical resolution of the model layers leads to changes in the mean terminal velocities of rain and snow following Eqs. (19) and (20). When the pass through assumption is justifiable a consistent way to estimate the average mixing ratios of precipitations is to use physically realistic mean terminal velocities (rather than \( \Delta z/\Delta t \)) in Eqs. (19) and (20). The use of \( \Delta z/\Delta t \) to convert
precipitation mixing ratios to fluxes is only valid when attaining the resultant fluxes produced by a layer within a time step.

To test the sensitivity of model simulations to the vertical resolution, we did not apply the nudging on water vapor and directly used the ECMWF temperatures so that the simulations have the same atmosphere state with the same temperature profile and water vapor forcing. Because we fixed the temperature profile for all of these simulations, the effects of differences caused by radiation calculations (i.e. heating rate effect) for different simulations were eliminated. We also let the model determine the saturation mixing ratio and partitioning of condensate only based on temperature so as to minimize differences associated with cloud prediction and partitioning of cloud water. Thus, we can isolate and evaluate the vertical resolution effect. Because the integrated ECMWF forcing is too strong (simulated precipitation is too large; also see Morrison and Pinto, 2004) and the water vapor was not constrained, the CSCM produced overcast cloudiness in all simulations. Fig. 6 shows results of a vertical resolution sensitivity study using these original treatments. (Only results shown in this figure are based on the original accretion parameterizations. All others are based on new accretion parameterizations that we discuss later. Figs. 3–5 are based on new accretion parameterizations but without considering accumulation effects.) Three vertical resolutions were used in the simulations. The legend “Model-oldacc-N” refers to the simulation with N vertical layers. The typical layer thickness in the troposphere for 30, 95 and 154 layers is 40–50mb, 7–8mb and 3–4mb, respectively. Fig. 6 shows that the predicted LWP and IWP systematically decrease when the vertical resolution increases.

An additional compounding problem is that the original scheme considers the accretion processes as a constant rate within each layer by using the fluxes (precipitation mixing ratio) at the top of each layer for the whole layer. A more physical way is to consider the accumulation effect within each layer, accounting for effects due to changes of precipitation within the same layer (precipitation flux increases as accretion occurs in the same layer). Here, we replaced the Beheng (1994) parameterization for accretion of cloud droplets by rain using Levkov et al. (1992) parameterization:

$$Q_{\text{rac}} = \frac{3}{2\rho_w D_{\text{RM}}} F_r q_{\text{cl}}$$  \hspace{1cm} (21)

where $\rho_w$ is the density of liquid water; $D_{\text{RM}} = 5.4 \times 10^{-4}$ m. The only thing we changed from Levkov et al. (1992) parameterization is to use the rain flux directly instead of the product of the rainwater mixing ratio and the mean terminal velocity of raindrops and air density.
We changed the parameterization of accretion of cloud droplets by snow to the Rotstayn (1997) parameterization:

\[ Q_{saci} = \frac{E_{ac} \lambda_d}{2 \rho_s} F_s q_{ci} \]  

(22)

where \( E_{ac} \) is the mean value of collection efficiency, which we set to 1 based on Rogers and Yau (1989) and Lin et al. (1983); \( \lambda_d = 1.6 \times 10^3 \cdot 10^{-0.023(T_0-7)} \) is the slope factor with \( T_0 = 273.16 \text{ K} \) and \( T \) is the absolute temperature of the atmosphere layer; \( \rho_s \) is the bulk density of snow which is set to 100 kg/m\(^3\).

The parameterization of the accretion of snow by ice crystals according to Levkov et al. (1992) is based on Lin et al. (1983):

\[ Q_{saci} = \pi \cdot q_{ci} \cdot E_s \rho_n os \cdot 3.078 \cdot \left[ \frac{\rho q_n / (\pi \rho_s n o s)}{(\rho_0 / \rho)^{0.25}} \right]^{0.8125} \]  

\[ \cdot \left[ (\rho_0 / \rho)^{0.25} (F_s / V_t)^{0.8125} \right] \]  

(23a)

\[ Q_{saci} = \pi \cdot q_{ci} \cdot E_s \rho_n os \cdot 3.078 \cdot \frac{1}{(\pi \rho_s n o s)^{0.8125}} \cdot \left[ (\rho_0 / \rho)^{0.25} F_s \cdot C \right] \]  

(23b)

where \( V_t \) is the terminal velocity of snow which we set as 1 m/s. In order to account for the accumulation effect in a simple analytical way, we modified Eq. (23b) so that the flux is expressed as a linear factor in the parameterization:

\[ Q_{saci} = \pi \cdot q_{ci} \cdot E_s \rho_n os \cdot 3.078 \cdot \frac{1}{(\pi \rho_s n o s)^{0.8125}} \cdot \left[ (\rho_0 / \rho)^{0.25} F_s \cdot C \right] \]  

where \( C = V_t^{-0.8125} \cdot F_s^{-0.1875} \) is assumed to be approximately constant with a numerical value that is about 7 for \( F_s \) with units of kg/m\(^2\) s and \( V_t \) equal to 1 m/s.

A general equation for growth of the precipitation flux due to accretion processes is then of the following form:

\[ \frac{dF}{dz} = a(q_x) + b \cdot F \cdot q_x \]  

(25)

where \( F \) is the precipitation flux, \( a(q_x) \) is the increase of flux caused by either autoconversion or aggregation, \( q_x \) is the cloud water content which is assumed to be constant within one layer, and the second term of the right-hand side accounts for the accretion effect.

For example, for the growth of rain flux the \( a(q_x) \) is the autoconversion rate Eq. (34) and \( b \) is \( \frac{3}{2 \rho_s \rho_n os} \) based on Eq. (21). Taking all quantities except the flux to be constant for given layer, we can solve this equation analytically for the flux and thereby explicitly consider the accumulated effect of accretion. The solution for the flux at the bottom of a layer based on Eq. (25) is:

\[ F = F_0 \cdot \exp(b \cdot q_x \cdot \Delta z) + \frac{a(q_x)}{b \cdot q_x} \cdot [\exp(b \cdot q_x \cdot \Delta z) - 1] \]  

(26)

where \( F_0 \) is the flux at the top of the layer and \( \Delta z \) is its thickness.

Fig. 7 shows the sensitivity of the modified parameterization for the accretion processes as well as the accumulation effects. Here we show the results using the new accretion parameterizations with and without applying the analytic solution (Eq. (26)) with different vertical resolution. Comparing Figs. 6 and 7 shows that the modified treatments of accretion processes have much less sensitivity to the model vertical resolution. However, the accumulation effect from the predicted LWP and IWP is clearly evident. The simulation with 30 layers (low vertical resolution) using the new parameterizations but without considering the accumulation effect systematically produces larger values of the LWP and IWP than the others, but the results of simulations with 95 and 154 layers show evidence of convergence. By applying Eq. (26) in the modified parameterizations, the simulated LWP and IWP show little sensitivity to the model vertical resolution, which achieving a magnitude slightly smaller than that using 154 layers without applying (26). This demonstrates that unphysical dependence of the accretion parameterization on the vertical resolution is eliminated by considering the accumulation effect. A similar effect, discussed by Rotstayn (1997), which needs to be considered when using a larger time step, is that cloud water content decreases with time when accretion processes are active. This is not considered in our study since we use a relative short time step.

### 4.2. Ice nucleation number concentration

Generally, there are three kinds of ice nucleation processes: Deposition and condensation-freezing nucleation, contact freezing and other secondary ice production. In the C SCM, the ice crystal nucleation is parameterized in terms of the newly deposited/frozen
ice water and a mean ice crystal radius derived from the effective ice crystal radius \( r_{ie} \) which is parameterized as a function of temperature based on observations (Ou and Liou, 1995):

\[
r_{ie} = 0.5 \times 10^{-6} \sqrt{326.3 + 12.4(T - T_0)} + 0.2(T - T_0) + 0.001(T - T_0)^3
\]

where \( T_0 = 273.16 \) K. The mean volume radius \( r_{iv} \) is determined based on an empirical relation with the effective ice crystal radius \( r_{ie} \) from simultaneous measurements of the two radii (Lohmann et al., 1999):

\[
r_{iv} = \frac{10^{-6}}{\beta + (\gamma + \delta r_{ie}^{1/3})^{1/3}}
\]

where \( \beta = -2.261 \times 10^6 \), \( \gamma = 5.113 \times 10^6 \), \( \delta = 2.809 \times 10^3 \).

Following Lohmann et al. (1999), the rate of new ice crystals nucleation for given time step \( \Delta t \) is then given by

\[
Q_{nuci} = \frac{3 \rho_i d_{i, dep}}{4 \pi r_{iv}^3} \frac{1}{\Delta t} + Q_{nfr}
\]

where \( d_{i, dep} \) is the increase in the ice mixing ratio due to deposition of new ice crystals in a layer during the time step, \( \rho_i \) (500 kg/m\(^3\)) is the ice crystal density and \( \rho_0 \) is the air density. \( Q_{nfr} \) is the increase of ice particles due to the freezing of cloud water in 1/m\(^3\) s.

However, many GCM cloud microphysics schemes including those used in UK Met-Office Unified Model (Wilson and Ballard, 1999), ARCSCM (Morrison et al., 2003), and CSIRO GCM (Rotstayn, 1997), use diagnostic parameterizations for ice nuclei number concentrations based on observations (Fletcher, 1962; Meyers et al., 1992). The parameterization developed by Meyers et al. (1992) considers the number concentration of ice nuclei due to deposition and condensation-freezing nucleation along with contact freezing:

\[
N_{nuci, dep} = 1000 \exp \left[ -0.639 + 0.1296(100(S_i - 1)) \right]
\]

\[
N_{nuci, con} = 1000 \exp \left[ -2.8 + 0.262(T_0 - T) \right]
\]

where \( T_0 = 273.16 \) K and \( S_i \) is the super-saturation ratio with respect to ice. \( N_{nuci, dep} \) and \( N_{nuci, con} \) are in the unit of 1/m\(^3\). Eq. (31) applies only if cloud liquid water is present. After comparing the Lohmann et al. (1999) treatment with Meyers et al. (1992) parameterization, we found that the Lohmann et al. (1999) treatment overestimates the number concentration of ice nuclei significantly and thus the CSCM produces much more ice particles with smaller sizes. This reduces conversion of ice particles to snow through the aggregation process. Consequently, the CSCM predicts much larger IWPs than those observed.
Fig. 8 shows the comparison of ice nucleation number concentration simulated by using Lohmann et al. (1999) treatment (Eqs. (27)–(29)) and Meyers et al. (1992) parameterization (Eqs. (30) and (31)). The solid line refers to the mean ice nucleation number concentration produced following Meyers et al. (1992) and the dash line with circles refers to Lohmann et al. (1999) treatment. They are the mean values of ice nucleation number concentration produced in each step versus temperature by the model during one simulation. It is evident that using Lohmann et al. (1999) treatment overestimates the nucleation number concentration significantly.

Fig. 9 shows results of the sensitivity study for ice nucleation number concentration. We used different treatments for ice nucleation number concentration with new accretion parameterizations (accumulation effects are not considered here). Simulations are based on general conditions (nudging on temperature and water vapor with adjusted water vapor profiles). The “Model-Meyers” refers the simulation using Meyers et al. (1992) parameterization and “Model-Lohmann” refers the simulation using Lohmann et al. (1999) treatment. Fig. 9 clearly shows that using Meyers et al. (1992) parameterization decreases the simulated IWP as compared to using Lohmann et al. (1999) treatment. With similar TCC and PREP prediction, the use of Meyers et al. (1992) parameterization brings the simulated IWP into a better agreement with that derived from measurements.

4.3. Autoconversion

Autoconversion is a highly nonlinear process. GCMs usually parameterize this process as a nonlinear function of in-cloud liquid water content. In the GCM cloud scheme tested in this study, the Beheng (1994) parameterization is used. As discussed by Pincus and Klein (2000) and Wood et al. (2002), this kind of nonlinear parameterization based on the mean cloud water content underestimates the autoconversion rate due to GCM sub-grid scale variability. Because the distribution of cloud water is not homogenous, using the linear averaging of water content to calculate such nonlinear process rate usually produces less precipitation. A more consistent way is to integrate the autoconversion rate by considering the probability distribution function (PDF) of cloud liquid water content. We have evaluated the sensitivity to such a procedure by using Gaussian PDF for total water to derive the factor that accounts for the effect of sub-grid variability as a function of cloud fraction. We then apply this correction factor to Beheng (1994) parameterization for auto-conversion in GCM grid scale.

For given GCM grid size, the cloud fraction $A$ and grid mean total cloud water content $q_c$ (Smith, 1990; Richard and Royer, 1993) can be expressed as:

$$A = \int_{-\infty}^{\infty} G(t) dt$$  \hspace{1cm} (32)
where \(t\), \(\sigma\) and \(Q_1\) are a normalized variable, its standard deviation, and a variable which states the threshold of condensation, respectively. The Beheng (1994) parameterization for autoconversion is:

\[
Q_{\text{aut}} = 6 \times 10^{28} \times 10^{-1.7} (10^{-9} N_i)^{-3.3} (10^{-3} \rho q_{cl})^{4.7} / \rho
\] (34)

where \(q_{cl}\) is the in-cloud liquid water mixing ratio and \(\rho\) is the density of air. We define the ratio \(R\) for the effect of horizontal inhomogeneity:

\[
R_{\text{aut}} = -40 \cdot A^3 + 89 \cdot A^2 - 93 \cdot A + 47
\] (36)

Fig. 10 shows the comparisons of CSCM simulations with modified microphysics parameterizations at different levels. They include the results using the Meyers et al. (1992) parameterization with modified treatments for accretion processes (“Model-Meyers”), the results using “Model-Meyers” but with treatments of accumulation effect (“Model-Meyers-ana”), and the results of further considering horizontal inhomogeneity effect (“Model-Meyers-ana-inhomo”).

With the consideration of accumulation effects, the predicted IWP decreases systematically. In November, March and April, the decreases are about 40% and in summer time (July–September 1998) the decreases are about 25%. The LWP decreases about 10% in the summer. We also see that, after accounting for the sub-grid variability effect on the Beheng (1994) autoconversion parameterization, in July and August the simulated LWP decreases additionally about 10% but simulated IWP increases a little bit. The TCC and PRED predictions agree with observations well for all
simulations, which are insensitive to the microphysics processes. We conclude that the simulated IWP with modified microphysics parameterizations (i.e., Model-Meyers-ana-inhomo) agree with the observations within observational uncertainties (Shupe, personal communication). The simulated LWP is also greatly improved. But it is noted that there still exist significant discrepancies between the simulated LWP and observations in July and August.

5. Partitioning of condensate in mixing clouds

The condensation/deposition of mixed phase clouds is a common source of difficulty in large-scale models. How to determine the total condensate and the partitioning between different phases is not well understood. This involves two separate issues. One is how to determine the water vapor saturation mixing ratio in mixed phase clouds in climate models. The other is how to partition the condensate between liquid and ice. Many existing cloud schemes first define saturation mixing ratio and then partition the super-saturated water vapor between ice and water using a simple formula that depends on the temperature below freezing point (Smith, 1990; Rotstayn, 1997; Fowler et al., 1996; Ose, 1993). The CSCM employs the saturation mixing ratio with respect to pure liquid or pure ice based on a threshold of cloud ice water content. So the accuracy of prediction of ice water content also affects the condensation/deposition and partitioning processes. Since condensation and evaporation processes are much faster than deposition and sublimation processes, it is commonly assumed the water vapor saturation pressure should always be that with respect to liquid as long as liquid water is present. But Fu and Hollars (2004) have shown, using in-situ aircraft observations from Canadian NRC Convair 580 during SHEBA/FIRE. ACE project, that the measured in-cloud water vapor pressure is in good agreement with the cloud-water weighed saturation pressure. One explanation for this result is that in mixed phase clouds there are small patches with liquid cloud parcels and ice cloud parcels intermingled so that the sampling counts the mean water vapor pressure of these patched clouds as a mixture. We have examined the sensitivity to the effect of the partitioning of mixed clouds in CSCM simulations by comparing the effect of using the original CSCM representation for total condensate and its partitioning to the one that is based on Fu and Hollars (2004) result. We did not nudge water vapor so that the two simulations have the exactly same forcing profiles for water vapor. We also scaled the moisture forcing data to fit the precipitation. Thus, we have the water vapor forcing whose integrated value is same as the
precipitation measured. The nudging on temperature is still retained so as to inhibit possible drifts associated with changes in temperature that may render interpretation of the results more difficult.

Fig. 11 shows the difference between the two simulations. Here all previous modifications on parameterizations are applied (Eqs. (21), (22), (24), (26), (30), (31) and (36)). We ignored the nudging on water vapor and scale the forcing using observed precipitation so that the integrated forcing is similar to observed precipitation. Providing a reasonable forcing and without constraining on water vapor we can test how well the microphysics parameterization works as compared with measurements. The ‘Model-ori-par’ refers to the results using original partitioning method (Lohmann and Roecker 1996; Lohmann et al., 1999) and ‘Model-mass-par’ refers to the mass-weighted partitioning method (Fu and Hollars, 2004). Using mass-weighted partitioning parameterization, the CSCM can produce LWP and IWP that agree well with observations, especially in the summer time for LWP. Although these results do not confirm unambiguously that the mass-weighted partitioning method is more reasonable, it clearly has the potential to explain why CSCM simulates an excessively large LWP in summertime in the SHEBA year.

6. Conclusions and summary

We have described some improvements of GCM cloud parameterizations and tested them in the context of the annual-cycle simulations for the SHEBA study. Using nudging techniques in CSCM simulations allows the CSCM to produce cloud and condensation based on the atmosphere that is close to the real atmosphere state; while allowing evaluation of simulated cloud properties (LWC, IWC, etc.) and their dependence on microphysics parameterizations. The main results are the following.

The CSCM simulations are very sensitive to the water vapor profile used for the nudging. Because the CSCM procedure for determining the saturation water vapor mixing ratio differs from that used for the ECMWF analyses, directly nudging using the SHEBA ECMWF reanalysis data results in a dryer background atmosphere during the simulations. In order to alleviate this bias for the Arctic simulations using the CSCM, we adjusted the water vapor profiles and used these for the nudging while retaining the original ECMWF reanalysis velocities and temperature profiles along with the adjusted water vapor profiles having similar relative humidity as rawinsonde observations. The simulation based on the new water vapor profiles leads to
reasonable predictions of cloud cover and surface precipitation.

The treatments of accretion processes were found to be flawed in various ways, resulting among other things in an unphysical dependence on vertical resolution. We changed and modified the parameterizations of the accretion processes to eliminate this artificial dependence on resolution as account as well for the effect of accumulation within layers.

The CSCM systematically tends to produce excessively large values of the IWP regardless of what water vapor profile is used in the nudging. This was found to be sensitive to the parameterization of the ice nucleation number concentration. The treatment following Lohmann et al. (1999), used in the standard version of the CSCM, results in an overestimation of ice nucleation number concentration in comparison with another commonly used parameterization (Meyers et al., 1992). This results in underestimate of mean ice particle size that decreases the aggregation rate evidently. Replacing the original treatment with the Meyers et al. (1992) parameterization results in more realistic simulated values of the IWP.

The CSCM uses the Beheng (1994) parameterization for autoconversion based on the average in-cloud liquid water content. As suggested by Pincus and Klein (2000), we considered the effect of sub-grid variability, which accounts the effect of unevenly distributed cloud water, in the context of an assumed Gaussian distribution for the totals water. Although the effect of doing this is relatively small, it does act to make the simulated LWP and IWP more realistic (smaller).

With modified cloud microphysics parameterizations including improved treatments for accretion processes, ice nucleation number concentration, and autoconversion, the CSCM simulated LWP and IWP are much improved as compared with observations. Furthermore, we find that the simulated LWP and IWP are also sensitive to the assumptions used to define saturated water vapor pressure and partition total cloud condensate in mixed phase clouds.

Using a partition and definition of the effective saturation vapor pressure based on Fu and Hollars (2004) resulted in substantially improved simulations of these quantities for the SHEBA location and period.

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