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X. Xie, Y. Liu

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Role of Microphysical Parameterizations with Droplet Relative Dispersion in IAP AGCM 4.1

Xiaoning XIE^{*1}, He ZHANG², Xiaodong LIU^{1,3}, Yiran PENG⁴, and Yangang LIU⁵

¹*State Key Laboratory of Loess and Quaternary Geology, Institute of Earth Environment, Chinese Academy of Sciences, Xi'an 710061*

²*International Center for Climate and Environment Sciences, Institute of Atmospheric Physics, Chinese Academy of Sciences, Beijing 100029*

³*University of Chinese Academy of Sciences, Beijing 100049*

⁴*Ministry of Education Key Laboratory for Earth System Modeling, Center for Earth System Science, and Joint Center for Global Change Studies (JCGCS), Tsinghua University, Beijing 100084*

⁵*Environmental and Climate Sciences Department, Brookhaven National Laboratory, Upton, New York 11973-5000, USA*

*Corresponding author : Xiaoning XIE
Email: xnxie@ieecas.cn

ABSTRACT

Previous studies have shown that accurate descriptions of the cloud droplet effective radius (R_e) and the autoconversion process of cloud droplets to raindrops (Au) can effectively improve simulated clouds and surface precipitation, and reduce the uncertainty of aerosol indirect effects in global climate models (GCMs). In this paper, we implement cloud microphysical schemes including two-moment Au and R_e considering relative dispersion of the cloud droplet size distribution into version 4.1 of the Institute of Atmospheric Physics atmospheric GCM (IAP AGCM 4.1), which is the atmospheric component of the Chinese Academy of Sciences-Earth System model (CAS-ESM 1.0). Analysis of the effects of different schemes shows that the newly implemented schemes can improve both the simulated shortwave (SWCF) and longwave cloud radiative forcings (LWCF) as compared to the standard scheme in IAP AGCM 4.1. The new schemes also effectively enhance the large-scale precipitation, especially over low latitudes, although the influences of total precipitation are insignificant for different schemes. Further studies show that similar results can be found with the Community Atmosphere Model 5.1 (CAM5.1).

Key words: relative dispersion, effective radius, autoconversion process, global climate models.

1. Introduction

Global climate models (GCMs) have suffered from a largest uncertainty in aerosol indirect effects and tend to overestimate the cooling of the aerosol indirect forcing according to IPCC (2007, 2013). Reducing the GCM uncertainty and reconciling GCMs

with observations are still major persistent challenges despite of several decades of research (e.g., Anderson et al., 2003; Quess et al., 2006; IPCC, 2013). Previous studies have shown that accurate descriptions of the cloud droplet effective radius (R_e) and the autoconversion process of cloud droplets to raindrops (Au) can effectively improve simulated clouds and surface precipitation and reduce the uncertainty of aerosol indirect effects in GCMs (Boucher et al., 1995; Lohmann and Feichter, 1997; Liu and Daum, 2002; 2004; Rotstayn and Liu, 2003; 2005; Liu et al., 2007; Xie and Liu, 2009).

Cloud droplet relative dispersion ε (defined as the ratio of the standard deviation to the mean droplet radius) is increased with increasing cloud droplet number concentration due to increasing anthropogenic aerosols because more numerous small droplets formed in polluted clouds compete for water vapor and broaden the droplet size distribution compared with clean clouds having fewer droplets and less competition (Liu and Daum, 2002). This enhanced ε reduces the changes induced by aerosols in the cloud droplet effective radius and the liquid water path, exerts a warming effect, and in turn partly offsets the cooling of aerosol indirect radiative forcing (Liu and Daum, 2002; Xie et al., 2017). Hence, parameterizations of R_e and Au considering the dispersion effect have been proposed to investigate aerosol indirect effect (Liu and Daum, 2002; 2004; Peng and Lohmann, 2003; Rotstayn and Liu, 2003; Liu et al., 2007; 2008; Xie and Liu, 2009; 2013). Liu and Daum (2002) related R_e to ε and further parameterized ε in terms of empirical relationship with cloud droplet number concentration showing that the magnitude of aerosol indirect radiative forcing can be reduced significantly in considering with the dispersion effect. Implementation of this parameterization of R_e with ε into various GCMs including CSIRO Mark3 GCM (Rotstayn and Liu, 2003) and

ECHAM4 (Peng and Lohmann, 2003) largely confirmed the results by Liu and Daum (2002). Autoconversion process determines the onset of the surface precipitation associated with warm clouds, and its parameterization has always attracted much attention. In recent years, the one-moment in mass content (e.g., Planche et al., 2015; Lee and Baik, 2017) and two-moment schemes in mass content and droplet concentration (e.g., Sednev and Menon, 2012; Kovačević and Ćurić, 2014; Michibata and Takemura, 2015) of autoconversion are also applied to different scale numerical models. Additionally, Liu and Duam (2004) developed an analytical autoconversion rate for mass content that accounts explicitly for ε using the generalized mean value theorem of integrals into the general collection equation. Extension of this theoretical expression to include the autoconversion threshold and autoconversion rate for cloud droplet number concentration were derived by Liu et al. (2006; 2007) and Xie and Liu (2009). The parameterization of Au in mass content with ε has been used in CSIRO Mark3 GCM (Rotstayn and Liu, 2005) and in the Weather Research and Forecast (WRF) model (Xie and Liu, 2011; Xie et al., 2013; Xie and Liu, 2015). Recently, the cloud microphysical schemes with two-moment Au and R_e with ε have been successfully implemented into a GCM of the Community Atmosphere Model 5.1 (CAM5.1), significantly reducing the aerosol indirect forcing, especially over the Northern Hemisphere (Xie et al., 2017).

IAP AGCM 4.1 is the latest version of IAP AGCM, which is the atmospheric component of the Chinese Academy of Sciences-Earth System model (CAS-ESM 1.0), developed at the Institute of Atmospheric Physics (IAP), Chinese Academy of Sciences (CAS) and described by Zhang et al. (2013) and Lin et al. (2016). IAP AGCM 4.1 adopted the physical package with a two-moment bulk stratiform cloud microphysics

scheme from CAM5.1 described by Morrison and Gettelman (2008) but has a different dynamical core (Zhang et al., 2009; 2013). Although the CAM5.1 microphysics schemes consider dispersion effect on cloud droplet effective radius with different expression from Liu and Daum (2002), they do not include the dispersion effect on the autoconversion processes of cloud droplets to raindrops (Xie et al., 2017). Hence, the cloud microphysical scheme including two-moment Au and R_e with ε are implemented into IAP AGCM 4.1, following Xie et al. (2017) for CAM5.1. To demonstrate the superiority of new schemes, we also evaluate the performance and improvement of IAP AGCM 4.1 by comparing the results with observations and CAM5.1 simulations, especially for the cloud shortwave (SWCF) and longwave radiative forcings (LWCF), and the surface precipitation.

This paper, as an extension to the preliminary study of Xie et al. (2017), describes the IAP AGCM 4.1 including the cloud microphysical schemes with two-moment Au and R_e with ε and set-up of the simulations in section 2; we evaluate the simulated cloud fields and surface precipitation against observations in IAP AGCM 4.1 with different cloud schemes, and also compare results between IAP AGCM 4.1 and CAM5.1 in section 3. Main conclusions and discussion are summarized in section 4.

2. Description of IAP AGCM 4.1 and simulations

2.1. *Description of IAP AGCM 4.1*

The GCM used in the present study is IAP AGCM 4.1 described by Zhang et al. (2013) and Lin et al. (2016), which can reproduce the observed climatology in a generally successful manner (Sun et al., 2012; Yan et al., 2014; Lin et al., 2016). The IAP AGCM

4.1 is a global grid-point model used finite-difference scheme with a terrain-following σ coordinate. This GCM horizontal resolution is about 1.4° latitude $\times$ 1.4° longitude and has 30 vertical levels with the model top at 2.2 hPa. The dynamical core from IAP AGCM 4.1 was described detailedly by Zhang et al. (2009; 2013). The physical processes in the IAP AGCM4.1 mostly come from the CAM5 (Neale et al., 2010), including a two-moment bulk stratiform cloud microphysics scheme coupled with a 3-mode version of the modal aerosol model, which is allowed to effectively investigate the aerosol direct and semi-direct effects, as well as indirect effects (Morrison and Gettelman, 2008; Liu et al., 2012; Ghan et al., 2012). Parameterizations of all the microphysical processes (Morrison and Gettelman, 2008) are adopted in this model including activation of cloud condensation nuclei or nucleation on ice nuclei to form cloud droplets or cloud ice, condensation/deposition, evaporation/sublimation, autoconversion of cloud droplets and ice to form rain and snow, accretion of cloud droplets and ice by rain, accretion of cloud droplets and ice by snow, heterogeneous freezing of cloud droplets to form ice, homogeneous freezing of cloud droplets, sedimentation, melting, and convective detrainment. Here, the autoconversion process is parameterized by Khairoutdinov and Kogan (2000), which is labeled by KK parameterization.

2.2. Newly implemented parameterizations for effective radius and autoconversion process

The R_e is parameterized via the following expression based on the assumption of cloud droplet size distribution following a gamma distribution (Liu and Daum, 2002; Xie and Liu, 2013)

$$R_e = \left(\frac{3}{4\pi\rho_w}\right)^{1/3} \frac{(1+2\varepsilon^2)^{2/3}}{(1+\varepsilon^2)^{1/3}} \left(\frac{L_c}{N_c}\right)^{1/3}, \quad (1)$$

138 where L_c (g cm^{-3}) and N_c (cm^{-3}) represent the liquid water mass content and cloud droplet
 139 number concentration for clouds, respectively; and ρ_w is the density of liquid water. The
 140 two-moment scheme of Au with ε can be easily derived from the analytical formulas
 141 (Xie and Liu, 2009). The number and mass autoconversion rates P_N and P_L can be
 142 written as:

$$143 \quad P_N = 1.1 \times 10^{10} \frac{\Gamma(\varepsilon^{-2}, x_{cq}) \Gamma(\varepsilon^{-2} + 6, x_{cq})}{\Gamma^2(\varepsilon^{-2} + 3)} L_c^2, \quad (2a)$$

$$144 \quad P_L = 1.1 \times 10^{10} \frac{\Gamma(\varepsilon^{-2}) \Gamma(\varepsilon^{-2} + 3, x_{cq}) \Gamma(\varepsilon^{-2} + 6, x_{cq})}{\Gamma^3(\varepsilon^{-2} + 3)} N_c^{-1} L_c^3, \quad (2b)$$

145 where

$$146 \quad x_{cq} = \left[\frac{(1 + 2\varepsilon^2)(1 + \varepsilon^2)}{\varepsilon^4} \right]^{1/3} x_c^{1/3} \quad (2c)$$

$$147 \quad x_c = 9.7 \times 10^{-17} N_c^{3/2} L_c^{-2} \quad (2d)$$

148 The Gamma function and the incomplete Gamma function can be represented as the
 149 following two formulas $\Gamma(n) = \int_0^\infty x^{n-1} \exp(-x) dx$ and $\Gamma(n, a) = \int_a^\infty x^{n-1} \exp(-x) dx$,
 150 respectively. The autoconversion rates about P_N and P_L both increase with L_c and ε
 151 but with N_c (Liu et al., 2007; Xie and Liu, 2009). The above cloud microphysical
 152 schemes of R_e and two-moment Au have been successfully implemented into the CAM5.1
 153 (Xie et al., 2017). Here, we implement these cloud schemes into IAP AGCM 4.1, where
 154 the Rotstayn-Liu relationship with $\varepsilon = 1 - 0.7 \exp(-0.003 N_c)$ is adopted in our model
 155 (Rotstayn and Liu, 2003) instead of the default relationship with
 156 $\varepsilon = 0.0005714 N_c + 0.271$ (Morrison and Gettelman, 2008). The default relationship is
 157 based on a small number of measurements ($\varepsilon = 0.43$ for polluted continent and $\varepsilon = 0.33$
 158 for clean ocean), whereas the Rotstayn-Liu relationship is derived from more

measurements described by Liu and Daum (2002). Note that the KK parameterization is fitted by applying the least squares method based on the results from a Large-Eddy Simulation, which apparently does not include the relative dispersion. However, our autoconversion parameterizations with ε were analytically derived by applying the generalized mean value theorem for integrals to the general collection equation (Xie and Liu, 2009). These autoconversion parameterizations used here are more reliable in physics, which were extended from one moment (Liu and Daum, 2004) to two-moment schemes (Xie and Liu, 2009).

2.3. Set up of IAP AGCM 4.1 simulations

We ran IAP AGCM 4.1 for the years from 1979 to 2005 with historical sea ice concentrations and sea surface temperature derived from Hurrell et al. (2008), and with historical greenhouse gases and anthropogenic aerosol emissions (Lamarque et al., 2010). Natural aerosols including sea salt and dust are predicted during this time period. To examine the influences of various cloud microphysical schemes on cloud microphysical fields and surface precipitation, two numerical experiments were performed with the standard and new cloud microphysical schemes. The standard experiment (Standard) uses the default cloud microphysical scheme of IAP AGCM 4.1; the new experiment (New) was conducted by use of the complete cloud schemes of R_e (1) and two-moment Au (2) with the Rotstayn-Liu relationship between ε and cloud droplet concentration.

3. Main results from IAP AGCM 4.1

Annual simulated global-mean cloud microphysical properties, surface precipitation and aerosol optical depth from IAP AGCM 4.1 (Standard and New) and corresponding

observations are shown in Table 1, including the vertically integrated cloud droplet
 number concentration (CDNUMC), liquid water path (LWP), ice water path (IWP), cloud
 droplet effective radius at cloud top (REL), total cloud amount (CLDTOT), low cloud
 fraction (CLDLOW), middle cloud fraction (CLDMID), high cloud fraction (CLDHGH),
 cloud optical thickness (COT), SWCF, LWCF, total precipitation (large-scale +
 convective precipitation, PRECT), and aerosol optical depth (AOD). The global annual
 mean values of CDNUMC are $1.24 \times 10^{10} \text{ m}^{-2}$ from Standard and $1.16 \times 10^{10} \text{ m}^{-2}$ from New,
 both significantly smaller than that based on AVHRR satellite observation ($4.01 \times 10^{10} \text{ m}^{-2}$)
 from an area between 50°S and 50°N by Han et al. (1998). The underestimated
 CDNUMC can be partly explained by the fact that the CDNUMC in CAM5.1 only
 includes contribution from stratiform clouds (Wang et al., 2011). The CDNUMC from
 New experiment is smaller than that from Standard experiment because of its larger
 autoconversion efficiency in New, especially at low levels over low latitudes due to
 higher cloud liquid water content (in Figure 1). The simulated LWP from New is given as
 39.03 g m^{-2} , which is much lower than that from Standard (50.14 g m^{-2}). It is also resulted
 from the changes in the autoconversion efficiency. The Standard and New share similar
 global annual mean IWP (18.62 g m^{-2} for Standard and 18.60 g m^{-2} for New). The REL in
 New is $12.40 \text{ }\mu\text{m}$, falling within the observational range from $11.4 \text{ }\mu\text{m}$ to $15.7 \text{ }\mu\text{m}$ (Han et
 al, 1998; Platnick et al., 2003). The REL is $9.86 \text{ }\mu\text{m}$ in Standard, which is much lower
 than New and observations. The simulated CLDTOT (66.63%) in New is larger than that
 (63.84%) in Standard, which just falls within the observational range from 65% to 75%
 based on ISCCP, MODIS, and HIRS data (Rossow and Schiffer, 1999; Platnick et al.,
 2003; Wylie et al., 2005). The increased CLDTOT in New is mainly due to the increased

high cloud fraction. This is because that the autoconversion rate in New is significantly decreased compared to Standard at high levels due to lower cloud water content (Figure 1), resulting in larger high cloud fraction. The COT is significantly decreased from 13.34 in Standard to 9.28 in New, resulted from the decreased LWP in New.

Observational cloud radiative forcings including SWCF and LWCF are derived from the CERES-EBAF satellite product from 2000 to 2010 described by Loeb et al. (2009) and the ERBE data from 1985 to 1989 described by Barkstrom and Hall (1982). The simulated SWCFs in annual global mean are -51.49 W m^{-2} in Standard and -48.31 W m^{-2} in New, showing that the global mean SWCF in New is lower than that in Standard. The main reason is that there exists lower cloud liquid water at low levels over low latitudes in New, leading to smaller SWCF. These two values fall within the observational range given by CERES-EBAF (-47.07 W m^{-2}) and ERBE (-54.16 W m^{-2}). The simulated LWCFs are 22.78 W m^{-2} in Standard and 23.56 W m^{-2} in New, which are lower than the observational values from Loeb et al. (2009) and Barkstrom and Hall (1982). However, the value of LWCF in New is much closer to the observational range of $26.48\text{-}30.36 \text{ W m}^{-2}$ compared to that in Standard. The increased LWCF in New is due to larger high cloud fraction compared to Standard. Observational total precipitation rate is derived from the Global Precipitation Climatology Project (GPCP) observation from 1979 to 2009 described by Adler et al. (2003) and the CPC Merged Analysis of Precipitation (CMAP) observation from 1979 to 1998 described by Xie and Arkin (1997). The simulated total precipitation rate for annual global means are similar for Standard (2.95 mm day^{-1}) and New (2.97 mm day^{-1}), which are larger than that from the observational results ($2.67\text{-}2.69 \text{ mm day}^{-1}$) taken from the GPCP and CMAP observations.

The AODs of annual global means derived from Standard and New are 0.092 and 0.090, respectively in Table 1. Because the same anthropogenic emissions (black carbon, organics, and sulfate) from Lamarque et al. (2010) are adopted in these two experiments, there exist insignificant differences of simulated AODs between Standard and New, likely because of differences in the meteorological conditions. Both simulated AODs are significantly lower than that from remote sensing from satellite composite (ca. 0.15) (Kinne et al., 2006), showing that IAP AGCM 4.1 significantly underestimates AOD. The main reason for the underestimation of AOD is that the time period of the simulated AODs (1979-2005) differs from the satellite observations almost after the year of 2000. Additionally, the anthropogenic aerosol emissions derived from Lamarque et al. (2010) are substantially underestimated, especially over South Asia and East Asia (Liu et al., 2012).

In order to further explore differences between the effects of using different cloud microphysical schemes, we further compare SWCF, LWCF, and surface precipitation for annual and seasonal zonal means and global spatial distribution in the following subsections.

3.1 Evaluation of SWCF

Figure 2 shows zonal means of SWCF from observations (CERES-EBAF and ERBE) and IAP AGCM 4.1 (Standard and New) for the annual, summer (JJA: June-July-August), and winter (DJF: December-January-February) periods. The annual zonal mean tendencies of SWCF from Standard and New are in good agreement with CERES-EBAF and ERBE. Both simulated SWCFs are much overestimated in low latitudes, and much underestimated in middle and high latitudes from Figure 2a. Over the low latitude regions,

the simulated SWCF in New is decreased significantly compared to Standard and is clearly closer to CERES-EBAF and ERBE observations, whereas the Standard and New experiments show insignificant influences on SWCF over the middle and high latitude regions. It is noted that the autoconversion rate of mass content (2) is a cubic function of cloud liquid water content, whereas it has a lower order as 2.47 (Morrison and Gettelman, 2008). Hence, the autoconversion rate used here is larger than the autoconversion rate of CAM5.1, especially at larger cloud water (Figure 1), which leads to less liquid clouds, and smaller SWCF over low latitude regions. As similar with annual zonal means of SWCF, the simulated seasonal ones in New are also significantly reduced in low latitudes, which are much in better agreement with the two observations in Figures 2b and 2c. Also noteworthy is that there exists a significant difference in SWCF between the two observational data in Figure 2a, with the zonal mean value from ERBE being much larger than that from CERES-EBAF.

Figure 3 shows the annual mean global spatial distribution of SWCF from CERES-EBAF for the years 2000-2010, IAP AGCM 4.1 of Standard and New, and model SWCF biases. The simulated annual mean SWCFs from Standard (Figure 3b) and New (Figure 3c) can both reproduce the spatial distribution of CERES-EBAF (Figure 3a). In Figures 3d and 3e, over low latitudes, the simulated SWCFs from Standard and New are much overestimated; and over middle and high latitudes, it is much underestimated as compared with CERES-EBAF. The model bias of annual mean SWCF for New is significantly reduced over low-latitude regions, where this reduced bias of SWCF is also found for JJA and DJF (not shown). Additionally, Table 2 summarized the statistical variables of SWCF about global means, the difference of global means between

observational estimates and model results, spatial pattern correlation, and root mean squared error (RMSE) for ANN, JJA, and DJF. This table shows that the annual, JJA, and DJF global mean SWCF in New is much closer to the CERES-EBAF estimates than that in Standard. The spatial pattern correlation is slightly increased in ANN, JJA, and DJF, and the RMSE (12.92, 15.26 and 18.20 W m^{-2} for ANN, JJA, and DJF, respectively) all decrease substantially in New, compared to that (15.54, 18.32, and 20.19 W m^{-2}) in Standard.

These results indicate that, compared to the standard cloud scheme, the new cloud schemes with ε can better simulate the SWCF, which effectively reduce the low-latitude SWCF and is much closer to satellite observations.

3.2 Evaluation of LWCF

The annual, JJA and DJF zonal mean LWCF from CERES-EBAF and ERBE, and IAP AGCM 4.1 are displayed in Figure 4. It shows that compared to the SWCF, influences of the cloud schemes on LWCF are much smaller. The simulated LWCF in New is slightly enhanced due to increased high cloud fraction and closer to observations over every latitude compared to Standard in annual (Figure 4a), JJA (Figure 4b), DJF (Figure 4c) means. For the annual (Figure 5) and seasonal (not shown) mean global spatial distribution of LWCF, the simulated results also can reproduce the observational spatial distribution. However, it is noted that differences of spatial distribution in LWCF are insignificant between Standard and New.

Table 2 shows that, compared to Standard, the model biases of LWCF for annual and seasonal global means in New can be significantly reduced against CERES-EBAF. Additionally, the spatial pattern correlation is increased slightly for annual and seasonal

means in New, and the RMSE are decreased. Hence, the above results show that the new cloud scheme improves the simulation of LWCF by increasing LWCF slightly.

3.3 Evaluation of surface precipitation

Figure 6 presents the annual and seasonal zonal mean of total precipitation rates and corresponding large-scale precipitation rates from observations of GPCP and CMAP and IAP AGCM 4.1 of Standard and New. Both Standard and New simulations can reproduce the annual and seasonal zonal mean changes of total precipitation with GPCP and CMAP in Figures 6a, 6c, and 6e. Furthermore, it shows that the simulated total precipitation rate in New is insignificantly influenced with respect to that in Standard for annual, JJA and DJF means. Differences in the global spatial distribution of the model biases for annual and seasonal total precipitation between Standard and New are also marginal (figures not shown). Additionally, Table 2 also shows that the model biases of annual and seasonal global mean total precipitation, the spatial pattern correlation, and the RMSE are insignificantly changed in Standard and New. Hence, the results from IAP AGCM 4.1 show that various cloud microphysical schemes does not affect the total surface precipitation significantly.

Figures 6b, 6d, and 6f show that the effect of cloud schemes on large-scale precipitation is stronger than the effect on total precipitation. The new scheme displays more large-scale precipitation than the standard scheme for annual and seasonal means, especially over low-latitude regions. It is because that the autoconversion rate used here is larger than the autoconversion rate of CAM5.1, especially at higher cloud liquid water (Figure 1), leading to much more large-scale precipitation over low-latitude regions. The results about the enhanced large-scale precipitation in New can also be found in Table 3.

The combined results of Figure 6 further indicate the fact that the total precipitation is determined by convective precipitation whereby no aerosol indirect effects have been considered.

3.4 Comparison between IAP AGCM 4.1 and CAM5.1

Results from IAP AGCM 4.1 (Table 2) and CAM5.1 (Table 4) show that the simulated SWCFs with new cloud schemes over low-latitude regions are significantly reduced and are much closer to satellite observations, compared to the standard cloud scheme, which decreases model bias of mean SWCF, increases the spatial pattern correlation and decreases the RMSE on the global scale. Here, we also compare the simulated SWCF from IAP AGCM 4.1 and CAM5.1 with the new cloud scheme (Tables 2 and 4). IAP AGCM 4.1 with new scheme shows smaller bias of global mean SWCF for ANN (-1.23 W m^{-2}), JJA (-3.24 W m^{-2}), and DJF (0.79 W m^{-2}) than that (-3.94 W m^{-2} , -7.14 W m^{-2} and -1.37 W m^{-2} for ANN, JJA and DJF, respectively) in CAM 5.1. This model also has a higher spatial pattern correlation with CERES-EBAF (0.85, 0.90, and 0.90 for ANN, JJA and DJF) than CAM5.1 (0.77, 0.84, and 0.83). Additionally, the RSME for IAP AGCM 4.1 (12.92, 15.26, and 18.20 W m^{-2} for ANN, JJA and DJF) are smaller than CAM5.1 (15.74, 20.69, and 21.62 W m^{-2}). Furthermore, IAP AGCM 4.1 with the new schemes improves simulated LWCF as discussed in Subsection 3.2; no such improvement was found in in CAM5.1 with the new schemes. Although IAP AGCM 4.1 with the new schemes shows a larger bias of global mean LWCF, it exhibits higher spatial pattern correlation (0.90, 0.89, and 0.92 for ANN, JJA and DJF) than CAM5.1 (0.88, 0.85, and 0.89); and lower RMSE ($6.83, 9.00$ and 8.29 W m^{-2} for ANN, JJA and DJF) than CAM5.1 (7.12, 10.45, and 9.38 W m^{-2}).

Compared to the standard scheme, the large-scale precipitation and its ratio to total precipitation can be effectively enhanced in the new scheme for both GCMs in Table 3. Note that although the ratio of large-scale precipitation to total precipitation from both GCMs in tropics (30°S–30°N) are much lower than the Tropical Rainfall Measuring Mission satellite (TRMM) observational estimates (Dai, 2006), these two GCMs with the new schemes produce much higher large-scale precipitation, and larger ratio of large-scale precipitation to total precipitation, which is clearly closer to the TRMM observational estimates. Additionally, IAP AGCM 4.1 displays much more large-scale precipitation and higher ratio of large-scale precipitation to total precipitation than CAM5.1.

4. Conclusions and discussion

In this paper, the cloud microphysical schemes including two-moment Au and R_e with relative dispersion are implemented into IAP AGCM 4.1 by following Xie et al., (2017). It is shown that the new cloud schemes can better simulate both the SWCF and LWCF against satellite observations, as compared to the standard scheme in IAP AGCM 4.1. This GCM with new scheme can effectively enhance the large-scale precipitation, especially over low latitudes, although the influence of total precipitation is insignificant for different cloud schemes. Additionally, further studies from results of the CAM5.1 show that the CAM5.1 with new schemes also improve the simulations of SWCF compared to the standard scheme, and enhance the large-scale precipitation and its ratio to total precipitation.

The dispersion effect on aerosol indirect forcing (AIF) in CAM5.1 has been reported from differences between the simulations with present-day (PD) and pre-

industrial (PI) aerosol emissions in Xie et al., (2017), showing that the corresponding AIF with the dispersion effect considered can be reduced substantially by a range of 0.10 to 0.21 W m⁻² at the global scale and by a much bigger margin of 0.25 to 0.39 W m⁻² for the Northern Hemisphere. The dispersion effect on AIF in AGCM 4.1 will be reported from PD and PI experiments in the further study. It is noted that the Rotstayn-Liu relationship of $\varepsilon - N_c$ in the cloud microphysical schemes with ε is used in this study (Rotstayn and Liu, 2003). Different empirical formulas have been presented to stand for ε with respect to N_c , since atmosphere environmental factors, aerosol chemical and physical properties may influence the relative dispersion significantly (Liu et al., 2008; Xie et al. 2013; Xie et al., 2017). The effect of different $\varepsilon - N_c$ relationships on the IAP AGCM4.1 will also be accounted for.

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- 518

519 **Caption:**

520 **Table 1.** Annual global mean cloud microphysical properties, precipitation and aerosol
 521 optical properties from IAP AGCM 4.1 (Standard and New) and observations: the
 522 vertical integrated cloud droplet concentration (CDNUMC), liquid water path (LWP), ice
 523 water path (IWP), cloud droplet effective radius at cloud top (REL), total cloud amount
 524 (CLDTOT), low cloud fraction (CLDLOW), middle cloud fraction (CLDMID), high
 525 cloud fraction (CLDHGH), cloud optical thickness (COT), SWCF, LWCF, total
 526 precipitation rate (large-scale + convective precipitation , PRECT) and aerosol optical
 527 depth (AOD). Differences in the corresponding properties between New and Standard
 528 (New–Standard) are also shown here. Note that the values in brackets are the
 529 corresponding standard deviations of the properties.

530 **Table 2.** Global means and Model–OBS (differences of global means between
 531 observational estimates and model results), R (spatial pattern correlation), and RMSE
 532 (root mean squared error) of the modeling results compared to the observed SWCF (W m^{-2}),
 533 LWCF (W m^{-2}) from the CERES-EBAF estimates from 2000 to 2010 and total
 534 precipitation rate (PRECT, mm day^{-1}) from the GPCP data from 1979 to 2009 for ANN,
 535 JJA, DJF in IAP AGCM 4.1.

536 **Table 3.** Annually and seasonal global and tropical (30S–30N) large-scale precipitation
 537 rate (PRECL, mm day^{-1}), and ratio of large-scale precipitation to total precipitation for
 538 IAP AGCM 4.1 and CAM5.1 with different cloud parameterizations (Standard and New).

539 **Table 4.** Global means and Model–OBS (differences of global means between
 540 observational estimates and model results), R (spatial pattern correlation), and RMSE
 541 (root mean squared error) of further modeling results compared to the observed SWCF (W

m^{-2}), LWCF (W m^{-2}) from CERES-EBAF estimates from 2000 to 2010 and total precipitation rate (PRECT, mm day^{-1}) from the GPCP data from 1979 to 2009 for ANN, JJA, DJF in CAM5.1 from Xie et al., (2017). Noted that the New here is the same as the New3 with the Rotstayn-Liu relationship in Xie et al., (2017).

Fig. 1. (a) Autoconversion rates from KK and new autoconversion parameterizations for a fixed cloud droplet concentration of 100 cm^{-3} , and (b) difference in autoconversion rates between Standard and New experiments (New–Standard).

Fig. 2. (a) Annual, (b) JJA and (c) DJF zonal mean SWCF (positive represents cooling) derived from observations (CERES-EBAF estimates from 2000 to 2010 and ERBE data from 1985 to 1989) and IAP AGCM 4.1 (Standard and New).

Fig. 3. Annual mean global spatial distribution of SWCF (W m^{-2}) for (a) CERES-EBAF estimates from 2000 to 2010, and IAP AGCM 4.1 of (b) Standard and (c) New; and model SWCF biases for (d) Standard and (e) New.

Fig. 4. (a) Annual, (b) JJA and (c) DJF zonal mean LWCF (positive represents warming) from observations (CERES-EBAF estimates from 2000 to 2010 and ERBE data from 1985 to 1989) and IAP AGCM 4.1 (Standard and New).

Fig. 5. Annual mean global spatial distribution of LWCF (W m^{-2}) for (a) CERES-EBAF estimates from 2000 to 2010, and IAP AGCM 4.1 of (b) Standard and (c) New; and model LWCF biases for (d) Standard and (e) New.

Fig. 6. (a, b) Annual, (c, d) JJA and (e, f) DJF zonal mean precipitation rate (PRECT, mm day^{-1}) and larger-scale precipitation rate (PRECL, mm day^{-1}) from observations (GPCP for the years 1979-2009 and CMAP for the years 1979-1998) and IAP AGCM 4.1 (Standard and New).

Table 1. Annual global mean cloud microphysical properties, precipitation and aerosol optical properties from IAP AGCM 4.1 (Standard and New) and observations: the vertical integrated cloud droplet concentration (CDNUMC), liquid water path (LWP), ice water path (IWP), cloud droplet effective radius at cloud top (REL), total cloud amount (CLDTOT), low cloud fraction (CLDLOW), middle cloud fraction (CLDMID), high cloud fraction (CLDHGH), cloud optical thickness (COT), SWCF, LWCF, total precipitation rate (large-scale + convective precipitation , PRECT) and aerosol optical depth (AOD). Differences in the corresponding properties between New and Standard (New–Standard) are also shown here. Note that the values in brackets are the corresponding standard deviations of the properties.

Simulation	Standard	New	Difference	OBS
CDNUMC (10^{10} m^{-2})	1.24 (0.02)	1.16 (0.01)	–0.07 (0.01)	4.01 ^a
LWP (g m^{-2})	50.14 (0.60)	39.03 (0.42)	–11.12 (0.34)	–
IWP (g m^{-2})	18.62 (0.16)	18.60 (0.19)	–0.03 (0.13)	–
REL (μm)	9.86 (0.03)	12.41 (0.05)	2.54 (0.04)	11.4 to 15.7 ^b
CLDTOT (%)	63.84 (0.17)	66.63 (0.22)	2.79 (0.24)	65 to 75 ^c
CLDLOW (%)	42.72 (0.14)	44.02 (0.16)	1.31 (0.14)	–
CLDMID (%)	21.85 (0.16)	22.31 (0.18)	0.45 (0.12)	–
CLDHGH (%)	38.89 (0.30)	42.72 (0.32)	3.83 (0.28)	–
COT (–)	13.34 (0.17)	9.28 (0.07)	–4.06 (0.12)	–
SWCF (W m^{-2})	–51.49 (0.40)	–48.31 (0.40)	3.18 (0.15)	–47.07 to –54.16 ^d
LWCF (W m^{-2})	22.78 (0.23)	23.56 (0.22)	0.78 (0.13)	26.48 to 30.36 ^d
PRECT (mm day^{-1})	2.95 (0.01)	2.97 (0.01)	0.01 (0.01)	2.67 to 2.69 ^e
AOD (–)	0.092 (0.001)	0.090 (0.001)	–0.002 (0.001)	0.15 ^f

^a CDNUMC is obtained from the AVHRR data from 50°S to 50°N described by Han et al. (1998). ^b REL is taken from the ISCCP data described by Han et al (1998) and the MODIS data described by Platnick et al. (2003). ^c TCC is derived from the ISCCP data (Rossow and Schiffer, 1999), MODIS data (Platnick et al., 2003), and HIRS data (Wylie et al., 2005). ^d SWCF and LWCF are taken from the ERBE estimates from 1985 to 1989 (Kiehl and Trenberth, 1997) and the CERES-EBAF estimates from 2000 to 2010 (Loeb et al., 2009). ^e PRECT is taken from the CMAP data from 1979 to 1998 (Xie and Arkin 1997) and the GPCP data from 1979 to 2009 (Adler et al., 2003). ^f AOD is taken from remote sensing from satellite composite (Kinne et al., 2006).

Table 2. Global means and Model–OBS (differences of global means between observational estimates and model results), R (spatial pattern correlation), and RMSE (root mean squared error) of the modeling results compared to the observed SWCF (W m^{-2}), LWCF (W m^{-2}) from the CERES-EBAF estimates from 2000 to 2010 and total precipitation rate (PRECT, mm day^{-1}) from the GPCP data from 1979 to 2009 for ANN, JJA, DJF in IAP AGCM 4.1.

	OBS	Standard			New		
	Mean	Model-OBS	R	RMSE	Model-OBS	R	RMSE
ANN SWCF	−47.07	−4.41	0.83	15.54	−1.23	0.85	12.92
JJA SWCF	−44.36	−6.45	0.89	18.32	−3.24	0.90	15.26
DJF SWCF	−51.65	−2.28	0.88	20.19	0.79	0.90	18.20
ANN LWCF	26.48	−3.69	0.88	7.47	−2.91	0.90	6.83
JJA LWCF	26.60	−3.29	0.87	9.50	−2.51	0.89	9.00
DJF LWCF	26.16	−4.14	0.91	8.63	−3.33	0.92	8.29
ANN PRECT	2.67	0.29	0.85	1.14	0.30	0.86	1.14
JJA PRECT	2.70	0.31	0.83	1.54	0.34	0.83	1.55
DJF PRECT	2.67	0.28	0.86	1.35	0.29	0.87	1.32

Table 3. Annually and seasonal global and tropical (30S–30N) large-scale precipitation rate (PRECL, mm day⁻¹), and ratio of large-scale precipitation to total precipitation for IAP AGCM 4.1 and CAM5.1 with different cloud parameterizations (Standard and New).

	IAP AGCM 4.1		CAM5.1	
	Standard	New	Standard	New
	Global	Global	Global	Global
ANN PRECL	1.06 (44.7%)	1.09 (45.7%)	0.87 (38.6%)	0.89 (39.8%)
JJA PRECL	1.02 (41.3%)	1.05 (43.0%)	0.84 (36.3%)	0.86 (38.1%)
DJF PRECL	1.08 (50.9%)	1.11 (51.7%)	0.88 (46.4%)	0.91 (47.4%)
	30S–30N	30S–30N	30S–30N	30S–30N
ANN PRECL	0.48 (16.0%)	0.52 (17.7%)	0.30 (10.2%)	0.32 (11.9%)
JJA PRECL	0.47 (17.0%)	0.51 (19.7%)	0.31 (12.4%)	0.34 (15.0%)
DJF PRECL	0.52 (20.8%)	0.55 (22.1%)	0.33 (17.3 %)	0.36 (18.1%)

Table 4. Global means and Model–OBS (differences of global means between observational estimates and model results), R (spatial pattern correlation), and RMSE (root mean squared error) of the modeling results compared to the observed SWCF (W m^{-2}), LWCF (W m^{-2}) from CERES-EBAF estimates from 2000 to 2010 and total precipitation rate (PRECT, mm day^{-1}) from the GPCP data from 1979 to 2009 for ANN, JJA, DJF in CAM5.1 from Xie et al., (2017). Noted that the New here is the same as the New3 with the Rotstajn-Liu relationship in Xie et al., (2017).

	OBS	Standard	New				
	Mean	Model-OBS	R	RMSE	Model-OBS	R	RMSE
ANN SWCF	−47.07	−5.01	0.77	16.50	−3.94	0.77	15.74
JJA SWCF	−44.36	−8.62	0.84	22.03	−7.14	0.84	20.69
DJF SWCF	−51.65	−2.36	0.82	22.24	−1.37	0.83	21.62
ANN LWCF	26.48	−2.42	0.87	7.13	−1.11	0.88	7.12
JJA LWCF	26.60	−1.86	0.83	10.42	−0.56	0.85	10.45
DJF LWCF	26.16	−3.06	0.88	9.06	−1.75	0.89	9.38
ANN PRECT	2.67	0.29	0.86	1.09	0.30	0.87	1.06
JJA PRECT	2.70	0.34	0.81	1.67	0.35	0.83	1.62
DJF PRECT	2.67	0.28	0.85	1.41	0.28	0.86	1.40

Fig. 1. (a) Autoconversion rates from KK and new autoconversion parameterizations for a fixed cloud droplet concentration of 100 cm^{-3} , and (b) difference in autoconversion rates between Standard and New experiments (New–Standard).

Fig. 2. (a) Annual, (b) JJA and (c) DJF zonal mean SWCF (positive represents cooling) derived from observations (CERES-EBAF estimates from 2000 to 2010 and ERBE data from 1985 to 1989) and IAP AGCM 4.1 (Standard and New).

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