Evaluation of autoconversion and accretion enhancement factors in GCM warm-rain parameterizations using ground-based measurements at the Azores

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Abstract

A great challenge in climate modelling is how to parametrize sub-grid cloud processes, such as autoconversion and accretion in warm rain formation. In this study, we use ground-based observations and retrievals over the Azores to investigate the so-called enhancement factors, E_{auto} and E_{accr}, which are often used in climate models to account for the influences of sub-grid variances of cloud and precipitation water on the autoconversion and accretion processes. E_{auto} and E_{accr} are computed for different model resolutions. The calculated E_{auto} values increase from 1.96 (30 km) to 3.15 (120 km), and the calculated E_{accr} values increase from 1.53 (30 km) to 1.76 (180 km). Comparing the prescribed enhancement factors in Morrison and Gettleman (2008, MG08) to the observed ones, we found that a higher E_{auto} (3.2) at small grids and lower E_{accr} (1.07) are used in MG08, which helps to explain why most of the GCMs produce too frequent precipitation events but with too light precipitation intensity. The ratios of rain to cloud water mixing ratio at E_{accr}=1.07 and E_{accr}=2.0 are 0.063 and 0.142, respectively, further proving that the prescribed value of E_{accr}=1.07 used in MG08 is too small to simulate correct precipitation intensity. Both E_{auto} and E_{accr} increase when the boundary layer becomes less stable, and the values are larger in precipitating clouds (CLWP>75 gm^{-2}) than those in nonprecipiting clouds (CLWP<75 gm^{-2}). Therefore, the selection of E_{auto} and E_{accr} values in GCMs should be regime-dependent.

1. Introduction

Due to their vast areal coverage (Warren et al., 1986, 1988; Hahn and Warren, 2007) and strong radiative cooling effect (Hartmann et al., 1992; Chen et al., 2000), small changes in the coverage or thickness of marine boundary layer (MBL) clouds could change the radiative energy budget significantly (Hartmann and Short, 1980; Randall et al., 1984) or even offset the radiative effects produced by increasing greenhouse gases (Slingo, 1990). The lifetime of MBL clouds remains an issue in climate models (Yoo and Li, 2012; Jiang et al., 2012; Yoo et al., 2013; Stanfield et al., 2014) and represents one of the largest uncertainties in predicting future climate (Wielicki et al., 1995; Houghton et al., 2001; Bony and Dufresne, 2005).

MBL clouds frequently produce precipitation, mostly in the form of drizzle (Austin et al., 1995; Wood, 2005a; Leon et al., 2008; Wood, 2012). A significant amount of drizzle is evaporated before reaching the surface, for example, about ~76% over the Azores region in Northeast Atlantic (Wu et al., 2015), which provides another water vapour source for MBL clouds. Due to their pristine environment and their close vicinity to the surface, MBL clouds are especially sensitive to aerosol perturbations (Quaas et al., 2009; Kooperman et al., 2012). Most aerosol indirect effects are associated with precipitation suppression (Albrecht, 1989; Ackerman et al., 2004; Lohmann and Feichter, 2005; Wood, 2007). Thus, accurate prediction of precipitation is essential in simulating the global energy budget and in constraining aerosol indirect effects in climate projections.

Due to the coarse spatial resolutions of the general circulation model (GCM) grid, many cloud processes cannot be adequately resolved and must be parameterized. For example, warm rain parameterizations in most GCMs treat the condensed water as either cloud or rain from the collision-coalescence process, which is partitioned into autoconversion and accretion sub-processes in model parameterizations (Kessler, 1969; Tripoli and Cotton, 1980; Beheng, 1994; Khairoutdinov and Kogan, 2000; Liu and Daum, 2004). Autoconversion represents the process that drizzle drops being formed through the condensation of cloud droplets and accretion represents the process where rain drops grow by the coalescence of drizzle-sized drops with cloud droplets. Autoconversion mainly accounts for precipitation initiation while accretion primarily contributes to precipitation intensity. Autoconversion is often parameterized as functions of cloud droplet number concentration (N_c) and cloud water mixing ratio (q_c), while accretion depends on both cloud and rain water mixing ratios (q_c and q_r) (Kessler, 1969; Tripoli and Cotton, 1980; Beheng, 1994; Khairoutdinov and Kogan, 2000; Liu and Daum, 2004; Wood, 2005b). All previous studies suggested that these two processes as power law functions of cloud and precipitation properties (See section 2 for details).

In conventional GCMs, the lack of information on the sub-grid variances of cloud and precipitation leads to the unavoidable use of the grid-mean quantities ($\overline{N_c}$, $\overline{q_c}$, and $\overline{q_r}$, where overbar denotes grid mean, same below) in calculating autoconversion and accretion rates. MBL cloud liquid water path (CLWP) distributions are often positive skewed (Wood and

Hartmann, 2006; Dong et al., 2014a and 2014b), that is, the mean value is greater than mode value. Thus, the mean value only represents a relatively small portion of samples. Also, due to the nonlinear nature of the relationships, the two processes depend significantly on the sub-grid variability and co-variability of cloud and precipitation microphysical properties (Weber and Quass, 2012; Boutle et al., 2014). In some GCMs, sub-grid scale variability is often ignored or hard coded using constants to represent the variabilities under all meteorological conditions and across the entire globe (Pincus and Klein, 2000; Morrison and Gettleman, 2008; Lebsock et al., 2013). This could lead to systematic errors in precipitation rate simulations (Wood et al., 2002; Larson et al., 2011; Lebsock et al., 2013; Boutle et al., 2014; Song et al., 2018), where GCMs are found to produce too frequent but too light precipitation compared to observations (Zhang et al., 2002; Jess, 2010; Stephens et al., 2010; Nam and Quaas, 2012; Song et al., 2018). The bias is found to be smaller by using a probability density function (PDF) of cloud water to represent the sub-grid scale variability in autoconversion parameterization (Beheng, 1994; Zhang et al., 2002; Jess, 2010), or more complexly, by integrating the autoconversion rate over a joint PDF of liquid water potential temperature, vertical velocity, total water mixing ratio and rain water mixing ratio (Cheng and Xu, 2009).

Process rate enhancement factors (E) are introduced when considering sub-grid scale variability in parameterizing grid-mean processes and they should be parameterized as functions of the PDFs of cloud and precipitation properties within a grid box (Morrison and

Gettleman, 2008; Lebsock et al., 2013; Boutle et al., 2014). However, these values in some GCM parameterization schemes are prescribed as constants regardless of underlying surface or meteorological conditions (Xie and Zhang, 2015). Boutle et al. (2014) used aircraft in situ measurements and remote sensing techniques to develop a parameterization for cloud and rain, in which not only consider the sub-grid variabilities under different grid scales, but also consider the variation of cloud and rain fractions. The parameterization was found to reduce precipitation estimation bias significantly. Hill et al. (2015) modified this parameterization and developed a regime and cloud type dependent sub-grid parameterization, which was implemented to the Met Office Unified Model by Walters et al. (2017) and found that the radiation bias is reduced using the modified parameterization. Using ground-based observations and retrievals, Xie and Zhang (2015) proposed a scale-aware cloud inhomogeneity parameterization that they applied to the Community Earth System Model (CESM) and found that it can recognize spatial scales without manual tuning. The inhomogeneity parameter is essential in calculating enhancement factors and affect the conversion rate from cloud to rain liquid. Xie and Zhang (2015), however, did not evaluate the validity of CESM simulations from their parameterization; the effect of N_c variability or the effect of covariance of cloud and rain on accretion process was not assessed. Most recently, Zhang et al. (2018) derived the sub-grid CLWP and N_c from the MODIS cloud product. They also studied the implication of the sub-grid cloud property variations for the autoconversion rate simulation, in particular the enhancement factor, in GCMs. For the first time, the enhancement factor due to the sub-grid variation of N_c is derived from satellite observation, and results reveal several regions downwind of biomass burning aerosols (e.g., Gulf of Guinea, East Coast of South Africa), air pollution (i.e., Eastern China Sea), and active volcanos (e.g., Kilauea Hawaii and Ambae Vanuatu), where the enhancement factor due to N_c is comparable, or even larger than that due to CLWP. However, one limitation of Zhang et al. (2018) is the use of passive remote sensing data only, which cannot distinguish cloud and rain water.

Dong et al. (2014a and 2014b) and Wu et al. (2015) reported MBL cloud and rain properties over the Azores and provided the possibility of calculating the enhancement factors using ground-based observations and retrievals. A joint retrieval method to estimate q_c and q_r profiles is proposed based on existing studies and is presented in Appendix A. Most of the calculations and analyses in this study is based on Morrison and Gettleman (2008, MG08 hereafter) scheme. The enhancement factors in several other schemes are also discussed and compared with the observational results and the approach in this study can be repeated for other microphysics schemes in GCMs. This manuscript is organized as follows: section 2 includes a summary of the mathematical formulas from previous studies that can be used to calculate grid-mean process enhancement factors. Ground-based observations and retrievals are introduced in Section 3. Section 4 presents results and discussions, followed by summary and conclusions in Section 5. The retrieval method used in this study is in Appendix A.

2. Mathematical Background

Autoconversion and accretion rates in GCMs are usually parameterized as power law equations (Tripoli and Cotton, 1980; Beheng, 1994; Khairoutdinov and Kogan, 2000; Liu and Daum, 2004):

$$\left(\frac{\partial q_r}{\partial t}\right)_{auto} = A\overline{q_c}^{a1}\overline{N_c}^{a2}, \tag{1}$$

$$\left(\frac{\partial q_r}{\partial t}\right)_{accr} = B(\overline{q_c}\,\overline{q_r})^{b}, \tag{2}$$

where A, $a1$, $a2$, B, and b are coefficients in different schemes listed in Table 1. The $\overline{q_c}$, $\overline{q_r}$, and $\overline{N_c}$ are grid-mean cloud water mixing ratio, rain water mixing ratio, and droplet number concentration, respectively. Because it is widely used in model parameterizations, the detailed results from Khairoutdinov and Kogan (2000) parameterization that been used in MG08 scheme will be shown in Section 4 while a summary will be given for other schemes.

Ideally, the covariance between physical quantities should be considered in the calculation of both processes. However, $\overline{q_c}$ and $\overline{N_c}$ in Eq. (1) are arguably not independently retrieved in our retrieval method which will be introduced in this section and Appendix A. Thus we only assess the individual roles of q_c and N_c sub-grid variations in determining autoconversion rate. q_c and q_r, on the other hand, are retrieved from two independent algorithms as shown in Dong et al. (2014a and 2014b), Wu et al. (2015) and Appendix A, we will assess the effect of cloud and rain property covariance on accretion rate calculations.

In the sub-grid scale, the PDFs of q_c and N_c are assumed to follow a gamma distribution based on observational studies of optical depth in MBL clouds (Barker et al., 1996; Pincus et al., 1999; Wood and Hartmann, 2006):

$$P(x) = \frac{\alpha^{\nu}}{\Gamma(\nu)} x^{\nu-1} e^{-\alpha x} , \quad (3)$$

where x represents q_c or N_c with grid-mean quantity $\overline{q_c}$ or $\overline{N_c}$, represented by μ, $\alpha = \nu/\mu$ is the scale parameter, σ^2 is the relative variance of x (= variance divided by μ^2), $\nu = 1/\sigma^2$ is the shape parameter. ν is an indicator of cloud field homogeneity, with large values representing homogeneous and small values indicating inhomogeneous cloud field.

By integrating autoconversion rate, Eq. (1), over the grid-mean rate, Eq. (3), with respect to sub-grid scale variation of q_c and N_c, the autoconversion rate can be expressed as:

$$\left(\frac{\partial q_r}{\partial t}\right)_{auto} = A\mu_{q_c}^{a1}\mu_{N_c}^{a2}\frac{\Gamma(\nu+a)}{\Gamma(\nu)\nu^{a}}, \quad (4)$$

where a = a1 or a2. Comparing Eq. (4) to Eq. (1), the autoconversion enhancement factor (E_{auto}) can be given with respect to q_c and N_c:

$$E_{auto} = \frac{\Gamma(\nu+a)}{\Gamma(\nu)\nu^{a}} . \quad (5)$$

In addition to fitting the distributions of q_c and N_c, we also tried two other methods to calculate E_{auto}. The first is to integrate Eq. (1) over the actual PDFs from observed or retrieved parameters and the second is to fit a lognormal distribution for sub-grid variability like what has been done in other studies (e.g., Lebsock et al., 2013; Larson and Griffin, 2013). It is found that all three methods get similar results. In this study, we use a gamma distribution that is consistent with MG08. Also note that, in the calculation of E_{auto} from $\overline{N_c}$, the negative exponent (-1.79) may cause singularity problems in Eq. (5). When this situation occurs, we do direct calculations by integrating the PDF of $\overline{N_c}$ rather than using Eq. (5).

To account for the covariance of microphysical quantities in a model grid, it is difficult to apply bivariate gamma distribution due to its complex nature. In this study, the bivariate lognormal distribution of q_c and q_r is used (Lebsock et al., 2013; Boutle et al., 2014) and can be written as:

$$P(\overline{q_c},\ \overline{q_r}) = \frac{1}{2\pi\overline{q_c}\,\overline{q_r}\sigma_{q_c}\sigma_{q_r}\sqrt{1-\rho^2}} exp\left\{-\frac{1}{2}\frac{1}{1-\rho^2}\left[\left(\frac{ln\overline{q_c}-\mu_{q_c}}{\sigma_{q_c}}\right)^2 - 2\rho\left(\frac{ln\overline{q_c}-\mu_{q_c}}{\sigma_{q_c}}\right)\left(\frac{ln\overline{q_r}-\mu_{q_r}}{\sigma_{q_r}}\right) + \left(\frac{ln\overline{q_r}-\mu_{q_r}}{\sigma_{q_r}}\right)^2\right]\right\}, \tag{6}$$

where σ is standard deviation and ρ is the correlation coefficient of q_c and q_r.

Similarly, by integrating the accretion rate in Eq. (2) from Eq. (6), we get the accretion enhancement factor (E_{accr}) of:

$$E_{accr} = \left(1+\frac{1}{\nu_{q_c}}\right)^{\frac{1.15^2-1.15}{2}}\left(1+\frac{1}{\nu_{q_r}}\right)^{\frac{1.15^2-1.15}{2}} \exp(\rho 1.15^2\sqrt{\ln\left(1+\frac{1}{\nu_{q_c}}\right)\ln(1+\frac{1}{\nu_{q_r}})}). \tag{7}$$

3. Ground-based observations and retrievals

The datasets used in this study were collected at the Department of Energy (DOE) Atmospheric Radiation Measurement (ARM) Mobile Facility (AMF), which was deployed on the northern coast of Graciosa Island (39.09°N, 28.03°W) from June 2009 to December 2010 (for more details, please refer to Rémillard et al., 2012; Dong et al., 2014a and Wood et al., 2015). The detailed operational status of the remote sensing instruments on AMF was summarized in Figure 1 of Rémillard et al. (2012) and discussed in Wood et al. (2015). The ARM Eastern North Atlantic (ENA) site was established on the same island in 2013 and provides long-term continuous observations.

The cloud-top heights (Z_{top}) were determined from W-band ARM cloud radar (WACR) reflectivity and only single-layered low-level clouds with $Z_{top} \leq 3$ km are selected. Cloud-base heights (Z_{base}) were detected by a laser ceilometer (CEIL) and the cloud thickness was simply the difference between cloud top and base heights. The cloud liquid water path (CLWP) was retrieved from microwave radiometer (MWR) brightness temperatures measured at 23.8 and 31.4 GHz using a statistical retrieval method with an uncertainty of 20 g m^{-2} for CLWP < 200 g m^{-2}, and 10% for CLWP > 200 g m^{-2} (Liljegren et al., 2001; Dong et al., 2000). Precipitating status is identified through a combination of WACR reflectivity and Z_{base}. As in Wu et al. (2015), we labelled the status of a specific time as “precipitating” if the WACR reflectivity below the cloud base exceeds -37 dBZ.

The ARM merged sounding data have a 1-min temporal and 20-m vertical resolution below 3 km (Troyan, 2012). In this study, the merged sounding profiles are averaged to 5-min resolution. Pressure and temperature profiles are used to calculate air density (ρ_{air}) profiles and to infer adiabatic cloud water content.

Cloud droplet number concentration (N_c) is retrieved using the methods presented in Dong et al. (1998, 2014a and 2014b) and are assumed to be constant in a cloud layer. Vertical profiles of cloud and rain water content (CLWC and RLWC) are retrieved by combining WACR reflectivity, CEIL attenuated backscatter and by assuming adiabatic growth of cloud parcels. The detailed description is presented in Appendix A with the results from a selected case. The CLWC and RLWC values are transformed to q_c and q_r by dividing by air density (e.g., $q_c(z) = CLWC(z)/\rho_{air}(z)$).

The estimated uncertainties for the retrieved q_c and q_r are 30% and 18%, respectively (see Appendix A). We used the estimated uncertainties of q_r and q_c as inputs of Eqs. (4) and (7) to assess the uncertainties of E_{auto} and E_{accr}. For instance, $(1 \pm 0.3)q_c$ are used in Eq. (4) and the mean differences are then used as the uncertainty of E_{auto}. Same method is used to estimate the uncertainty for E_{accr}.

The autoconversion and accretion parameterizations partitioned from the collision-coalescence process dominate at different levels in a cloud layer. Autoconversion dominates around cloud top where cloud droplets reach maximum by condensation and accretion is dominant at middle and lower parts of the cloud where rain drops sediment and continue to grow by collecting cloud droplets. Complying with the physical processes, we estimate autoconversion and accretion rates at different levels of a cloud layer in this study. The averaged q_c within the top five range gates (~215 m thick) are used to calculate E_{auto}. To calculate E_{accr}, we use the averaged q_c and q_r within five range gates around the maximum radar reflectivity. If the maximum radar reflectivity appears at the cloud base, then five range gates above the cloud base are used.

The ARM merged sounding data are also used to calculate lower tropospheric stability (LTS), which is used to infer the boundary layer stability. In this study, unstable and stable boundary layers are defined as LTS less than 13.5 K and greater than 18 K, respectively, and environment with an LTS between 13.5 K and 18 K is defined as mid-stable (Wang et al. 2012; Bai et al. 2018). Enhancement factors in different boundary layers are summarized in Section 4.2 and may be used as references for model simulations. Further, two regimes are classified: CLWP greater than 75 g m^{-2} as precipitating and CLWP less than 75 g m^{-2} as nonprecipitating (Rémillard et al., 2012).

To evaluate the dependence of autoconversion and accretion rates on sub-grid variabilities for different model spatial resolutions, an averaged wind speed within a cloud layer was extracted from merged sounding and used in sampling observations over certain periods to mimic different grid sizes in GCMs. For example, two hours of observations corresponds to a

72-km grid box if mean in-cloud wind speed is 10 $m\ s^{-1}$ horizontal wind and if the wind speed is 5 $m\ s^{-1}$, four hours of observations is needed to mimic the same grid. We used six grid sizes (30-, 60-, 90-, 120-, 150-, and 180-km) and mainly show the results from 60-km and 180-km grid sizes in Section 4.

4. Results and discussions

In this section, we first show the data and methods using a selected case, followed by statistical analysis based on 19-month of data and multiple time-intervals.

4.1 Case study

The selected case occurred on July 27, 2010 (Figure 1a) at the Azores. This case was characterized by a long time of non-precipitating or light drizzling cloud development (00:00-14:00 UTC) before intense drizzling occurred (14:00-20:00 UTC). Wu et al. (2017) studied this case in detail to demonstrate the effect of wind shear on drizzle initiation. Here, we choose two periods corresponding to a 180-km grid and having similar mean q_c near cloud top: 0.28 g kg^{-1} for period c and 0.26 g kg^{-1} for period d but with different distributions (Figures 1c and 1d). The PDFs of q_c are then fitted using gamma distributions to get shape parameters (ν) as shown in Figures 1c and 1d. Smaller ν is usually associated with more inhomogeneous cloud field, which allows more rapid drizzle production and more efficient liquid transformation from cloud to rain (Xie and Zhang, 2015) in regions that satisfy precipitation criteria, which is usually controlled using threshold q_r, droplet size or relative humidity (Kessler, 1969; Liu and

Daum, 2004). The period d has a wider q_c distribution than the period c, resulting in a smaller ν and thus larger E_{auto}. Using the fitted ν, the E_{auto} from q_c is calculated from Eq. (5) and the period d is larger than the period c (1.80 vs. 1.33). The E_{auto} values for the periods d and c can also be calculated from N_c using the same procedure as q_c with similar result (2.1 vs. 1.51). The E_{accr} values for the periods d and c can be calculated from the covariance of q_c and q_r and Eq. (7). Not surprisingly, the period d has larger E_{accr} than the period c. The combination of larger E_{auto} and E_{accr} in the period d contributes to the rapid drizzle production and high rain rate as seen from WACR reflectivity and q_r.

It is important to understand the physical meaning of enhancement factors in precipitation parameterization. For example, if we assume two scenarios for q_c with a model grid having the same mean values but different distributions: (1) The distribution is extremely homogeneous, there will be no sub-grid variability because the cloud has the same chance to precipitate and the enhancement factors would be unity (this is true for arbitrary grid-mean q_c amount as well). (2) The cloud field gets more and more inhomogeneous with a broad range of q_c within the model grid box, which results in a greater enhancement factor and increases the possibility of precipitation. That is, a large enhancement factor can make the part of cloud with higher q_c within the grid box become more efficient in generating precipitation, rather than the entire model grid.

It is clear that q_c and N_c in Figure 1b are correlated with each other. In addition to their natural relationships, q_c and N_c in our retrieval method are also correlated (Dong et al., 2014a and 2014b). Thus, the effect of q_c and N_c covariance on E_{auto} is not included in this study. In Figures 1c and 1d, the results are calculated using model grid of 180-km for the selected case on 27 July 2010. In Section 4.2, we will use these approaches to calculate their statistical results for multiple grid sizes using the 19-month ARM ground-based observations and retrievals.

4.2 Statistical result

For a specific grid size, e.g. 60-km, we estimate the shape parameter (ν) and calculate E_{auto} through Eqns. (5) and (7). The PDFs of E_{auto} for both 60-km and 180-km grids are shown in Figures 2a-2d. The distributions of E_{auto} values calculated from q_c with 60-km and 180-km grid sizes (Figures 2a and 2b) are different to each other (2.79 vs. 3.3). The calculated E_{auto} values range from 1 to 10, and most are less than 4. The average value for the 60-km grid (2.79) is smaller than that for the 180-km grid (3.2), indicating a possible dependence of E_{auto} on model grid size. Because drizzle-sized drops are primarily resulted from autoconversion, we investigate the relationship between E_{auto} and precipitation frequency, which is defined as the average percentage of drizzling occurrence based on radar reflectivity below the cloud base. The precipitation frequency (black lines in Figures 2a and 2b) within each PDF bin shows an increasing trend for E_{auto} from 0 to 4-6, then oscillates around a relative constant when $E_{auto} > 6$, indicating that in precipitation initiation process, E_{auto} keeps increasing to a certain value

(~6) until the precipitation frequency reaches a near-steady state. Larger E_{auto} values do not necessarily result in higher precipitation frequency but instead may produce more drizzle-sized drops from autoconversion process when the cloud is precipitating. Therefore, the E_{auto} value of 6 is a critical threshold for converting cloud droplets into rain drops within MBL clouds in MG08.

The PDFs of E_{auto} calculated from N_c also share similar patterns of positive skewness and peaks at ~1.5-2.0 for the 60-km and 180-km grid sizes (Figures 2c and 2d). Although the average values are close to their q_c counterparts (2.54 vs. 2.79 for 60-km and 3.45 vs. 3.2 for 180-km), the difference in E_{auto} between 60-km and 180-km grid sizes becomes large. The precipitation frequencies within each bin are nearly constant or slightly decrease, which are different to their q_c counterparts shown in Figures 2a and 2b. This suggests complicated effects of droplet number concentration on precipitation initiation and warrants more explorations of aerosol-cloud-precipitation interactions. This is very intriguing result, which suggests the existence of significant sub-grid variation of N_c and this variation can significantly influence the warm rain process. As mentioned in Section 2, q_c and N_c are also fitted using lognormal distributions to calculate E_{auto}, those are close to the results in Figure 2 (not shown here) with average values of 3.28 and 3.84, respectively, for 60-km and 180-km grid sizes. Because the E_{auto} values calculated from q_c and N_c are close to each other, we will focus on analyzing the results from q_c only for simplicity and clarity. The effect of q_c and N_c covariance, as stated in

Section 4.1, is not presented in this study due to the intrinsic correlation in the retrieval (Dong et al., 2014a and 2014b and Appendix A of this study).

The covariance of q_c and q_r is included in calculating E_{accr} and the results are shown in Figures 2e and 2f. The calculated E_{accr} values range from 1 to 4 with mean values of 1.62 and 1.76 for 60-km and 180-km grid sizes, respectively. These two mean values are much greater than the prescribed value used in MG08 (1.07). Since accretion is dominant at middle and lower parts of the cloud where rain drops sediment and continue to grow by collecting cloud droplets, we superimpose the ratio of q_r to q_c within each bin (black lines in Figures 2e and 2f) to represent the portion of rain water in the cloud layer. In both panels, the ratios are less than 15%, which means that q_r can be one order of magnitude smaller than q_c. The differences in magnitude are consistent with previous CloudSat and aircraft results (e.g., Boutle et al., 2014). This ratio increases from E_{accr}=0 to ~2, and then decreases, suggesting a possible optimal state for the collision-coalescence process to achieve maximum efficiency for converting cloud water into rain water at E_{accr}=2. In other words, the conversion efficiency cannot be infinitely increased with E_{accr} under available cloud water. The ratios of q_r to q_c at E_{accr}=1.07 and E_{accr}=2.0 are 0.063 and 0.142, respectively, further proving that the prescribed value of E_{accr}=1.07 used in MG08 is too small to simulate correct precipitation intensity in the models. Therefore, similar to the conclusions in Lebsock et al. (2013) and Boutle et al. (2014), we suggest increasing E_{accr} from 1.07 to 1.5-2.0 in GCMs.

To illustrate the impact of using prescribed enhancement factors, autoconversion and accretion rates are calculated using the prescribed values (e.g., 3.2 for E_{auto} and 1.07 for E_{accr}, MG08; Xie and Zhang, 2015) and the newly calculated ones in Figure 2 that use observations and retrievals. Figure 3 shows the joint density of autoconversion (Figures 3a and 3b) and accretion rates (Figures 3c and 3d) from observations (x-axis) and model parameterizations (y-axis) for 60-km and 180-km grid sizes. Despite the spread, the peaks of the joint density of autoconversion rate appear slightly above the one-to-one line, suggesting that cloud droplets in the model are more easily to be converted into drizzle/rain drops than observations. On the other hand, the peaks of accretion rate appear slightly below the one-to-one line which indicates that simulated precipitation intensities are lower than observed ones. The magnitudes of the two rates are consistent with Khairoutdinov and Kogan (2000), Liu and Daum (2004), and Wood (2005b).

Compared to the observations, the precipitation in GCMs occurs at higher frequencies with lower intensities, which might explain why the total precipitation amounts are close to surface measurements over an entire grid box. This ‘promising’ result, however, fails to simulate precipitation on the right scale and cannot capture the correct rain water amount, thus providing limited information in estimating rain water evaporation and air-sea energy exchange.

Clouds in an unstable boundary layer have a better chance of getting moisture supply from the surface by upward motion than clouds in a stable boundary layer. Precipitation frequencies are thus different in these two boundary layer regimes. For example, clouds in a relatively unstable boundary layer seem easier to produce drizzle than those in a stable boundary layer (Wu et al., 2017). Provided the same boundary layer condition, CLWP is an important factor in determining the precipitation status of clouds. At the Azores, precipitating clouds are more likely to have CLWP greater than 75 g m^{-2} than their nonprecipitating counterparts (Rémillard et al., 2012). To further investigate what conditions and parameters can significantly influence the enhancement factors, we classify low-level clouds according to their boundary layer conditions and CLWPs.

The averaged E_{auto} and E_{accr} values for each category are listed in Table 2. Both E_{auto} and E_{accr} increase when the boundary layer becomes less stable, and these values become larger in precipitating clouds (CLWP>75 gm^{-2}) than those in nonprecipiting clouds (CLWP<75 gm^{-2}). In real applications, autoconversion process only occurs when q_c or cloud droplet size reaches a certain threshold (e.g., Kessler, 1969 and Liu and Daum, 2004). Thus, it will not affect model simulations if a valid E_{auto} is assigned to Eq. (1) in a nonprecipitating cloud. The E_{auto} values in both stable and mid-stable boundary layer conditions are smaller than the prescribed value of 3.2, while the values in unstable boundary layers are significantly larger than 3.2 regardless of if they are precipitating or not. All E_{accr} values are greater than the constant of 1.07. The E_{auto} values in Table 2 range from 2.32 to 6.94 and the E_{accr} values vary from 1.42 to 1.86, depending on different boundary layer conditions and CLWPs. Therefore, as suggested by Hill et al. (2015), the selection of E_{auto} and E_{accr} values in GCMs should be regime-dependent.

To properly parameterize sub-grid variabilities, the approaches by Hill et al. (2015) and Walters et al. (2017) can be adopted. To use MG08 and other parameterizations in GCMs as listed in Table 1, proper adjustments can be made according to the model grid size, boundary layer conditions, and precipitating status. As stated in the methodology, we used a variety of model grid sizes. Figure 4 demonstrates the dependence of both enhancement factors on different model grid sizes. The E_{auto} values (red line) increase from 1.97 at a grid box of 30×30 km to 3.15 at a grid box of 120×120 km, which are 38.4% and 2% percent lower than the prescribed value (3.2, upper dashed line). After that, the E_{auto} values remain relatively constant of ~3.18 when the model grid is 180 km, which is close to the prescribed value of 3.2 used in MG08. This result indicates that the prescribed value in MG08 represents well in large grid sizes in GCMs. The E_{accr} values (blue line) increase from 1.53 at a grid box of 30×30 km to 1.76 at a grid box of 180×180 km, those are 43% and 64%, respectively, larger than the prescribed value (1.07, lower dashed line). The shaded areas represent the uncertainties of E_{auto} and E_{accr} associated with the uncertainties of the retrieved q_c and q_r. When model grid size increases, the uncertainties slightly decrease. The prescribed E_{auto} is close to the upper boundary of uncertainties except for the 30-km grid size, while the prescribed E_{accr} is significantly lower than the lower boundary.

It is noted that E_{auto} and E_{accr} depart from their prescribed values at opposite directions as model grid size increases. For models with finer resolutions (e.g., 30-km), both E_{auto} and E_{accr} are significantly different from the prescribed values, which can partially explain the issue of 'too frequent' and 'too light' precipitation. Under both conditions, the accuracy of precipitation estimation is degraded. For models with coarser resolutions (e.g., 180-km), average E_{auto} is exactly 3.2 while E_{accr} is much larger than 1.07 when compared to finer resolution simulations. In such situations, the simulated precipitation will be dominated by the 'too light' problem, in addition to regime-dependent (Table 2) and as in Xie and Zhang (2015), E_{auto} and E_{accr} should be also scale-dependent.

Also note that the location we choose to collect ground-based observations and retrievals is on the remote ocean where the MBL clouds mainly form in a relatively stable boundary layer and are characterized by high precipitation frequency. Even in such environments, however, the GCMs overestimate the precipitation frequency (Ahlgrimm and Forbes, 2014).

To further investigate how enhancement factors affect precipitation simulations, we use E_{auto} as a fixed value of 3.2 in Eq. (4), and then calculate the q_c needed for models to reach the same autoconversion rate as observations. The q_c differences between models and observations are representing the amount of q_c needed for models to adjust to get a realistic autoconversion rate in the simulations. Similar to Figure 1, the PDFs of q_c differences (model – observation) are plotted in Figures 5a and 5b for 60-km and 180-km grid sizes. Figure 5c shows the average percentages of model q_c adjustments for different model grid sizes. The mode and average values for 30-km grid is negative, suggesting that models need to simulate lower q_c in general to get reasonable autoconversion rates. Lower q_c values are usually associated with smaller E_{auto} values that induce lower simulated precipitation frequency. On average, the percentage of q_c adjustments decrease with increasing model grid size. For example, the adjustments for finer resolutions (e.g., 30-60 km) can be ~20% of the q_c, whereas adjustments in coarse resolution models (e.g., 120 – 180 km) are relatively small because the prescribed E_{auto} (=3.2) is close to the observed ones (Figure 4) and when model grid size is 180-km, no adjustment is needed. The adjustment method presented in Figure 5, however, may change cloud water substantially and may cause variety of subsequent issues, such as altering cloud radiative effects and disrupting the hydrological cycle. The assessment in Figure 5 only provides a reference to the equivalent effect on cloud water by using the prescribed E_{auto} value as compared to those from observations.

All above discussions are based on the prescribed E_{auto} and E_{accr} values (3.2 and 1.07) in MG08. Whereas there are quite a few parameterizations that have been published so far. In this study, we list E_{auto} and E_{accr} for three other widely used parameterization schemes in Table 3, which are given only for 60-km and 180-km grid sizes. The values of the exponent in each scheme directly affect the values of the enhancement factors. For example, the scheme in Beheng (1994) has highest degree of nonlinearity and hence has the largest enhancement factors. The scheme in Liu and Daum (2004) is very similar to the scheme in Khairoutdinov and Kogan (2000) because both schemes have a physically realistic dependence on cloud water content and number concentration (Wood, 2005b). For a detailed overview and discussion of various existing parameterizations, please refer to Liu and Daum (2004), Liu et al. (2006a), Liu et al. (2004b) and Wood (2005b).

5. Summary

To better understand the influence of sub-grid cloud variations on the warm-rain process simulations in GCMs, we investigated the warm-rain parameterizations of autoconversion (E_{auto}) and accretion (E_{accr}) enhancement factors in MG08. These two factors represent the effects of sub-grid cloud and precipitation variabilities when parameterizing autoconversion and accretion rates as functions of grid-mean quantities. E_{auto} and E_{accr} are prescribed as 3.2 and 1.07, respectively, in the widely used MG08 scheme. To assess the dependence of the two parameters on sub-grid scale variabilities, we used ground-based observations and retrievals collected at the DOE ARM Azores site to reconstruct the two enhancement factors in different model grid sizes.

From the retrieved q_c and q_r profiles, the averaged q_c within the top five range gates are used to calculate E_{auto} and the averaged q_c and q_r within five range gates around maximum reflectivity are used to calculate E_{accr}. The calculated E_{auto} values from observations and retrievals increase from 1.96 at a grid box of 30×30 km to 3.15 at a grid box of 120×120 km. These values are 38% and 2% lower than the prescribed value of 3.2. The prescribed value in MG08 represents well in large grid sizes in GCMs. On the other hand, the E_{accr} values increase from 1.53 at a grid box of 30×30 km to 1.76 at a grid box of 180×180 km, which are 43% and 64% higher than the prescribed value (1.07). The higher E_{auto} and lower E_{accr} prescribed in GCMs help to explain the issue of too frequent precipitation events with too light precipitation intensity. The ratios of rain to cloud liquid water increase with increasing E_{accr} from 0 to 2, and then decrease after that, suggesting a possible optimal state for the collision-coalescence process to achieve maximum efficiency for converting cloud water into rain water at E_{accr}=2. The ratios of q_r to q_c at E_{accr}=1.07 and E_{accr}=2.0 are 0.063 and 0.142, further proving that the prescribed value of E_{accr}=1.07 is too small to simulate correct precipitation intensity in models.

To further investigate what conditions and parameters can significantly influence the enhancement factors, we classified low-level clouds according to their boundary layer conditions and CLWPs. Both E_{auto} and E_{accr} increase when the boundary layer conditions become less stable, and the values are larger in precipitating clouds (CLWP>75 gm^{-2}) than those in nonprecipiting clouds (CLWP<75 gm^{-2}). The E_{auto} values in both stable and mid-stable boundary layer conditions are smaller than the prescribed value of 3.2, while those in unstable boundary layers conditions are significantly larger than 3.2 regardless of whether or not the cloud is precipitating (Table 2). All E_{accr} values are greater than the prescribed value of 1.07.

Therefore, the selection of E_{auto} and E_{accr} values in GCMs should be regime-dependent, which also has been suggested by Hill et al. (2015) and Walters et al. (2017).

This study, however, did not include the effect of uncertainties in GCM simulated cloud and precipitation properties on sub-grid scale variations. For example, we did not consider the behavior of the two enhancement factors under different aerosol regimes, a condition which may affect precipitation formation process. The effect of aerosol-cloud-precipitation-interactions on cloud and precipitation sub-grid variabilities may be of comparable importance to meteorological regimes and precipitation status and deserves a further study. In addition, other factors may also affect precipitation frequency and intensity even under the same aerosol regimes and even if the clouds have similar cloud water contents. Wind shear, for example as presented in Wu et al. (2017), is an external variable that can affect precipitation formation. Further studies are needed to evaluate the role of the covariance of q_c and N_c in sub-grid scales on E_{auto} determinations, which is beyond the scope of this study and requires independent retrieval techniques.

Appendix A: Joint cloud and rain LWC profile estimation

If a time step is identified as non-precipitating, the cloud liquid water content (CLWC) profile is retrieved using Frisch et al. (1995) and Dong et al. (1998, 2014a and 2014b). The retrieved CLWC is proportional to radar reflectivity.

If a time step is identified as precipitatinging (maximum reflectivity below cloud base exceeds -37 dBZ), CLWC profile is first inferred from temperature and pressure in merged sounding by assuming adiabatic growth. Marine stratocumulus is close to adiabatic (Albrecht et a. 1990) and was used in cloud property retrievals in literature (e.g., Rémillard et al., 2013). In this study, we use the information from rain properties near cloud base to further constrain the adiabatic CLWC ($CLWC_{adiabatic}$).

Adopting the method of O'Connor et al. (2005), Wu et al. (2015) retrieved rain properties below cloud base (CB) for the same period as in this study. In Wu et al. (2015), rain drop size (median diameter, D_0), shape parameter (μ), and normalized rain droplet number concentration (N_W) are retrieved for the assumed rain particle size distribution (PSD):

$$n_r(D) = N_W f(\mu) \left(\frac{D}{D_0}\right)^{\mu} \exp[-\frac{(3.67+\mu)D}{\mathrm{D}_0}] \tag{A1}$$

To infer rain properties above cloud base, we adopt the assumption in Fielding et al. (2015) that N_W increases from below CB to within the cloud. This assumption is consistent with the *in situ* measurement in Wood (2005a). Similar as Fielding et al. (2015), we use constant N_W within cloud if the N_W decrease with height below CB. The μ within cloud is treated as constant and is taken as the averaged value from four range gates below CB. Another assumption in the retrieval is that the evaporation of rain drops is negligible from one range gate above CB to one range gate below CB thus we assume rain drop size is the same at the range gate below and above CB.

With the above information, we can calculate the reflectivity contributed by rain at the first range gate above CB ($Z_d(1)$) and the cloud reflectivity ($Z_c(1)$) is then $Z_c(1) = \mathrm{Z}(1) - \mathrm{Z_d}(1)$, where $\mathrm{Z}(1)$ is WACR measured reflectivity at first range gate above CB. Using cloud droplet number concentration (N_c) from Dong et al. (2014a and 2014b), CLWC at the first range gate above CB can be calculated through

$$Z_c(1) = 2^6 \int_0^{\infty} n_c(r) r^6 dr = \frac{36}{\pi^2 \rho_w^2} \frac{{CLWC(1)_{reflectivity}}^2}{N_c} \exp(9\sigma_x^2) \tag{A2}$$

where $n_c(r)$ is lognormal distribution of cloud PSD with logarithmic width σ_x which is set to a constant value of 0.38 (Miles et al., 2000), ρ_w is liquid water density.

We then compare the $CLWC_{adiabatic}$ and the one calculated from $CLWC_{reflectivity}$ at the first range gate above CB. A scale parameter (s) is defined as $s = \frac{CLWC_{reflectivity}(1)}{CLWC_{adiabatic}(1)}$ and the entire profile of $CLWC_{adiabatic}$ is multiplied by s to correct the bias from cloud sub-adiabaticity. Reflectivity profile from cloud is then calculated from Eq. (A2) and the remaining reflectivity profile from WACR observation is regarded as rain contribution. Rain particle size can then be calculated given that N_W and μ are known and rain liquid water content (RLWC) can be estimated.

There are two constrains used in the retrieval. One is that the summation of cloud and rain liquid water path (CLWP and RLWP) must be equal to the LWP from microwave radiometer observation. Another is that rain drop size (D_0) near cloud top myst be equal or greater than 50

μm and if D_0 is less than 50 μm, we decrease N_W for the entire rain profile within cloud and repeat the calculation until the 50 μm criteria is satisfied.

It is difficult to quantitatively estimate the retrieval uncertainties without aircraft in situ measurements. For the proposed retrieval method, 18% should be used as uncertainty for RLWC from rain properties in Wu et al. (2015) and 30% for CLWC from cloud properties in Dong et al. (2014a and 2014b). The actual uncertainty depends on the accuracy of merged sounding data, the detectability of WACR near cloud base and the effect of entrainment on cloud adiabaticity during precipitating. In the recent aircraft field campaign, the Aerosol and Cloud Experiments in Eastern North Atlantic (ACE-ENA) was conducted during 2017-2018 with a total of 39 flights over the Azores, near the ARM ENA site on Graciosa Island. These aircraft in situ measurements will be used to validate the ground-based retrievals and quantitatively estimate their uncertainties in the future.

Figure A1 shows an example of the retrieval results. The merged sounding, ceilometer, microwave radiometer, WACR and ceilometer are used in the retrieval. Whenever one or more instruments are not reliable, that time step is skipped, and this results in the gaps in the CLWC and RLWC as shown in Figures A1(b) and A1(c). When the cloud is classified as nonprecipitating, no RLWC will be retrieved as well. Using air density (ρ_{air}) profiles calculated from temperature and pressure in merged sounding, mixing ratio (q) can be calculated from LWC using $q(z) = LWC(z)/\rho_{air}(z)$.

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Table 1. The parameters of autoconversion and accretion formulations for four parameterizations.

	A	$a1$	$a2$	B	b
Khairoutdinov and Kogan (2000)	1350	2.47	-1.79	67	1.15
Liu and Daum (2004)	$1.3 \times 10\beta_6^6$, where $\beta_6^6 = [(r_v + 3)/r_v]^2$, r_v is mean volume radius. modification was made by Wood (2005b)	3	-1	N/A	N/A
Tripoli and Cotton (1980)	3268	7/3	-1/3	1	1
Beheng (1994)	3×10^{34} for $N_c < 200$ cm^{-3} 9.9 for $N_c > 200$ cm^{-3}	4.7	-3.3	1	1

Table 2. Autoconversion (left) and accretion (right) enhancement factors in different boundary layer conditions (LTS > 18 K for stable, LTS < 13.5 K for unstable and LTS within 13.5 and 18 K for mid-stable) and in different LWP regimes (LWP ≤ 75 g m^{-2} for non-precipitating and LWP > 75 g m^{-2} for precipitating).

LTS (K)	LWP ≤ 75 g m^{-2}	LWP > 75 g m^{-2}
> 18	2.32/1.42	2.75/1.52
(13.5, 18)	2.61/1.47	3.07/1.68
< 13.5	4.62/1.72	6.94/1.86

Table 3. Autoconversion and accretion enhancement factors (E_{auto} and E_{accr}) for the parameterizations in Table 1 except the Khairoutdinov and Kogan (2000) scheme. The values are averaged for 60-km and 180-km model grids.

	E_{auto}		E_{accr}	
	60-km	180-km	60-km	180-km
Liu and Daum (2004)	3.82	4.23	N/A	N/A
Tripoli and Cotton (1980)	2.46	2.69	1.47	1.56
Beheng (1994)	6.94	5.88	1.47	1.56

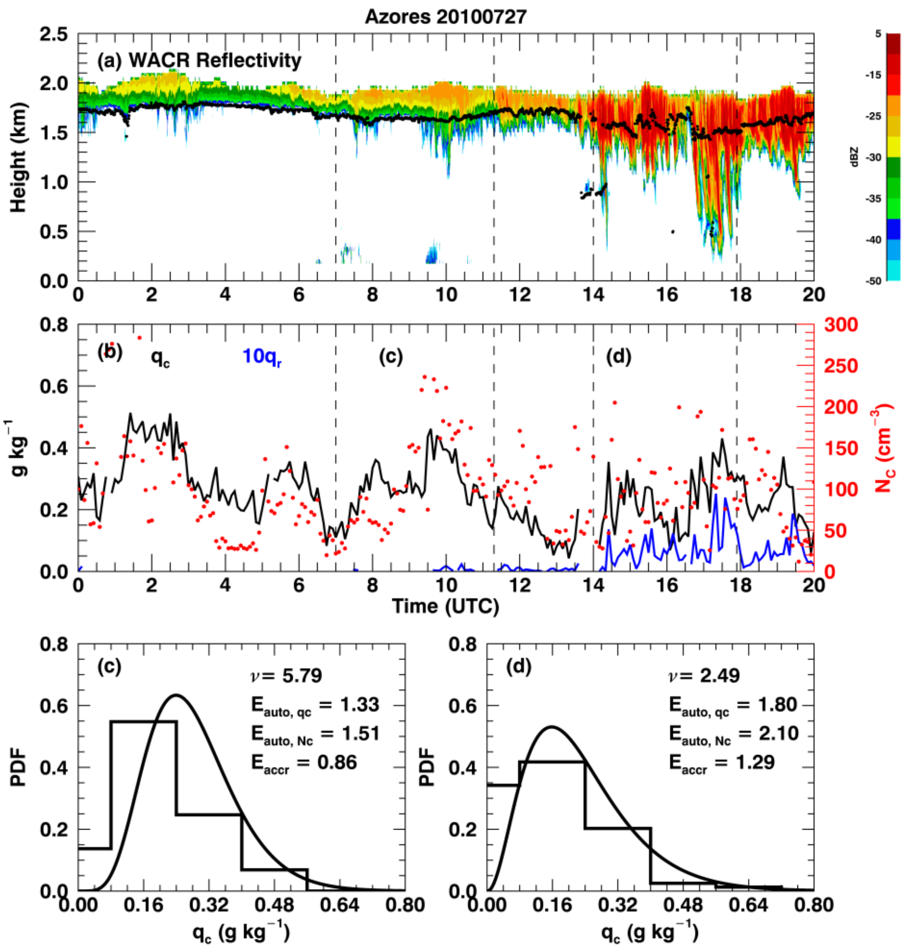

Figure 1. Observations and retrievals over Azores on 27 July 2010. (a) W-band ARM cloud radar (WACR) reflectivity (contour) superimposed with cloud-base height (black dots). (b) Black line represents averaged cloud water mixing ratio (q_c) within the top five range gates, blue line represents averaged rain (×10) water mixing ratio within five range gates around maximum reflectivity, red dots are the retrieved cloud droplet number concentration (N_c). Dashed lines represent two periods that have 60 km model grids with similar mean-q_c but different distributions as shown by step lines in (c) and (d). Curved lines in (c) and (d) are fitted gamma distributions with the corresponding shape parameter (ν) shown on the upper right. N_c distributions are not shown. The calculated autoconversion ($E_{auto,\ qc}$ from q_c and $E_{auto,\ Nc}$ from N_c) and accretion (E_{accr}) enhancement factors are also shown.

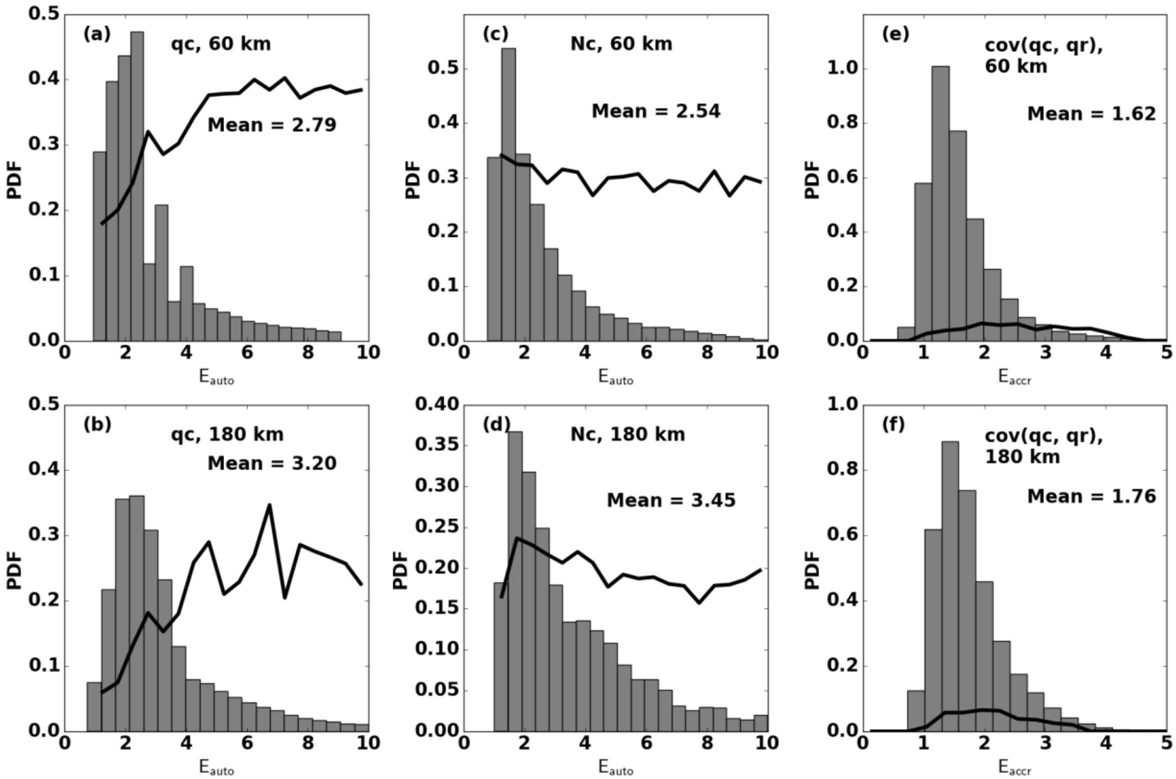

Figure 2. Probability density functions (PDFs) of autoconversion (a - d) and accretion (e - f) enhancement factors calculated from q_c (a-b), N_c (c-d), and the covariance of q_c and q_r (e-f). The two rows show the results from 60-km and 180-km model grids, respectively, with their average values. Black lines represent precipitation frequency in each bin in (a)-(d) and the ratio of layer-mean q_r to q_c in (e)-(f).

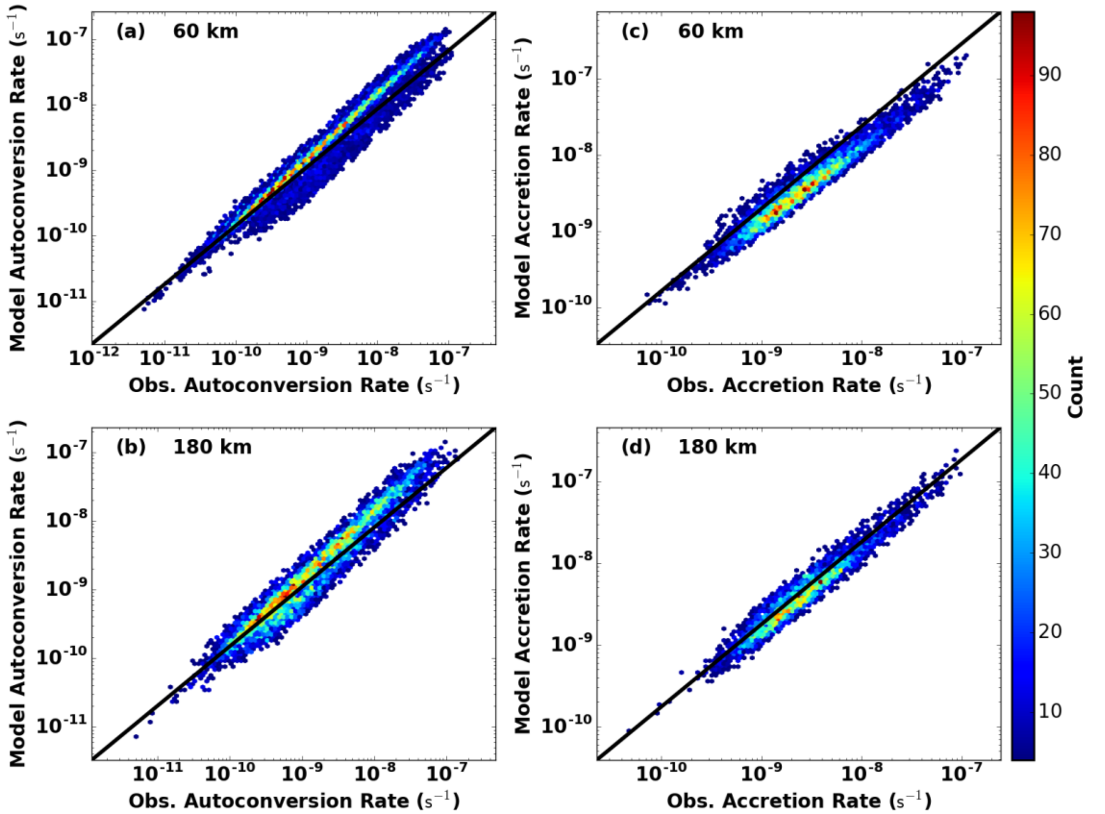

Figure 3. Comparison of autoconversion (a-b) and accretion (c-d) rates derived from observations (x-axis) and from model (y-axis). Results are for 60-km (a and c) and 180-km model grids. Colored dots represent joint number densities.

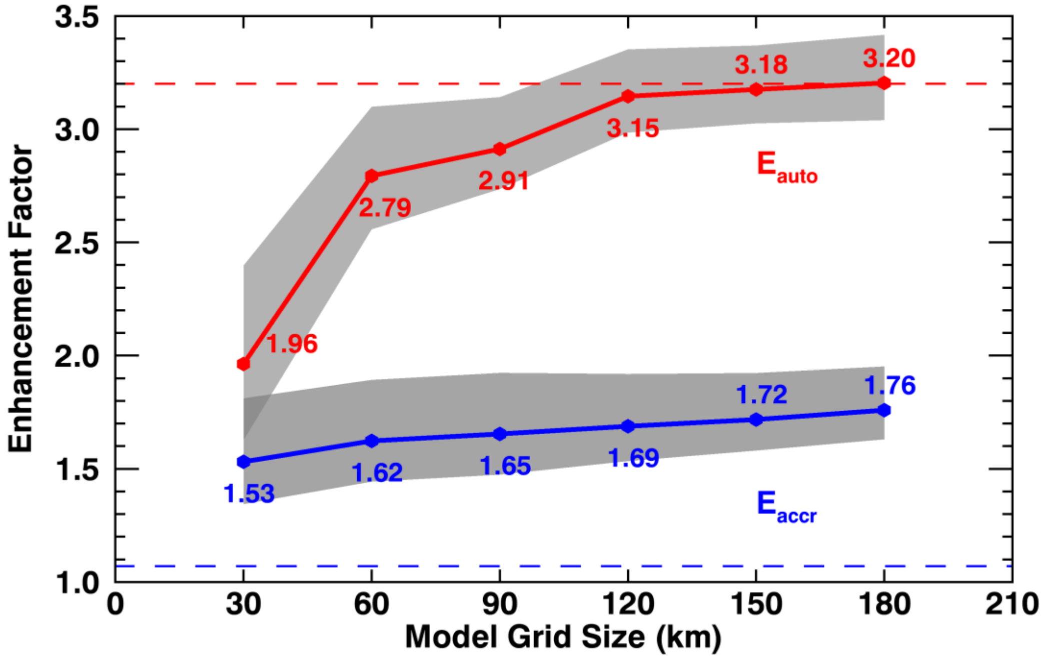

Figure 4. Autoconversion (red line) and accretion (blue line) enhancement factors as a function of model grid sizes. The shaded areas are calculated by varying q_c and q_r within their retrieval uncertainties. The two dashed lines show the constant values of autoconversion (3.2) and accretion (1.07) enhancement factors prescribed in MG08.

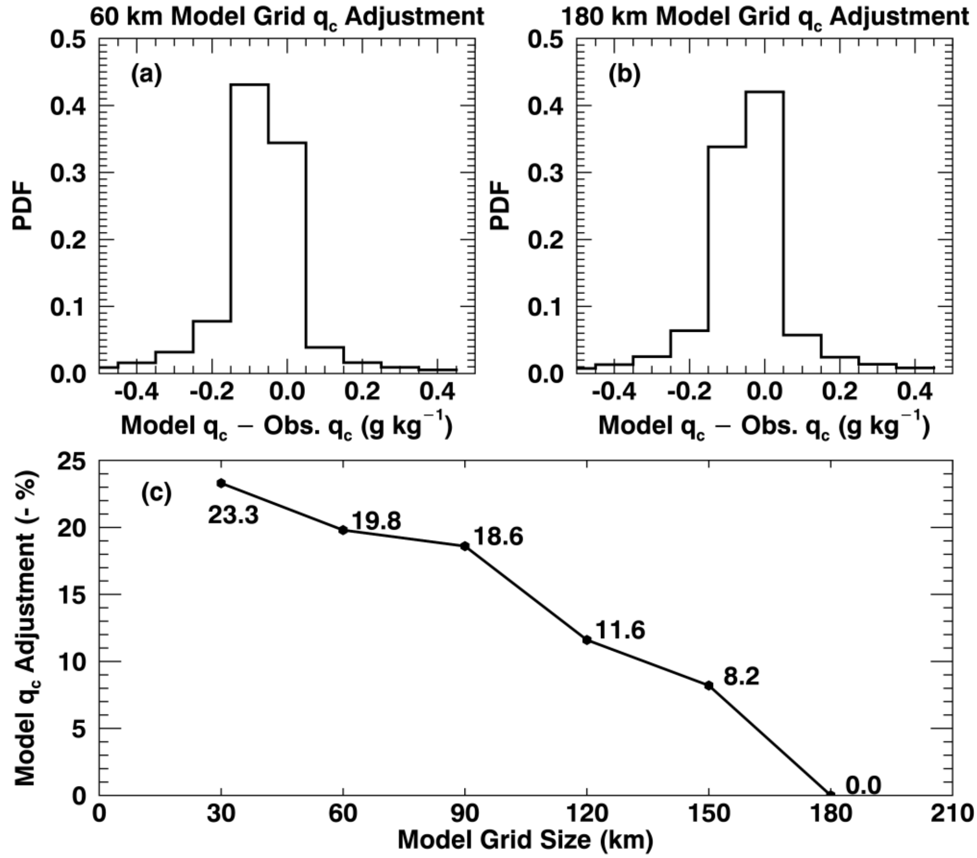

Figure 5. ***q_c*** **needed for models to adjust to reach the same autoconversion rate as observations for (a) 60-km and (b) 180-km model grids. Positive biases represent increased** ***q_c*** **are required in models and negative biases mean decreased** ***q_c*****. The average percentages of adjustments for different model grid sizes are shown in panel (c) and note that the percentages in the vertical axis are negative.**

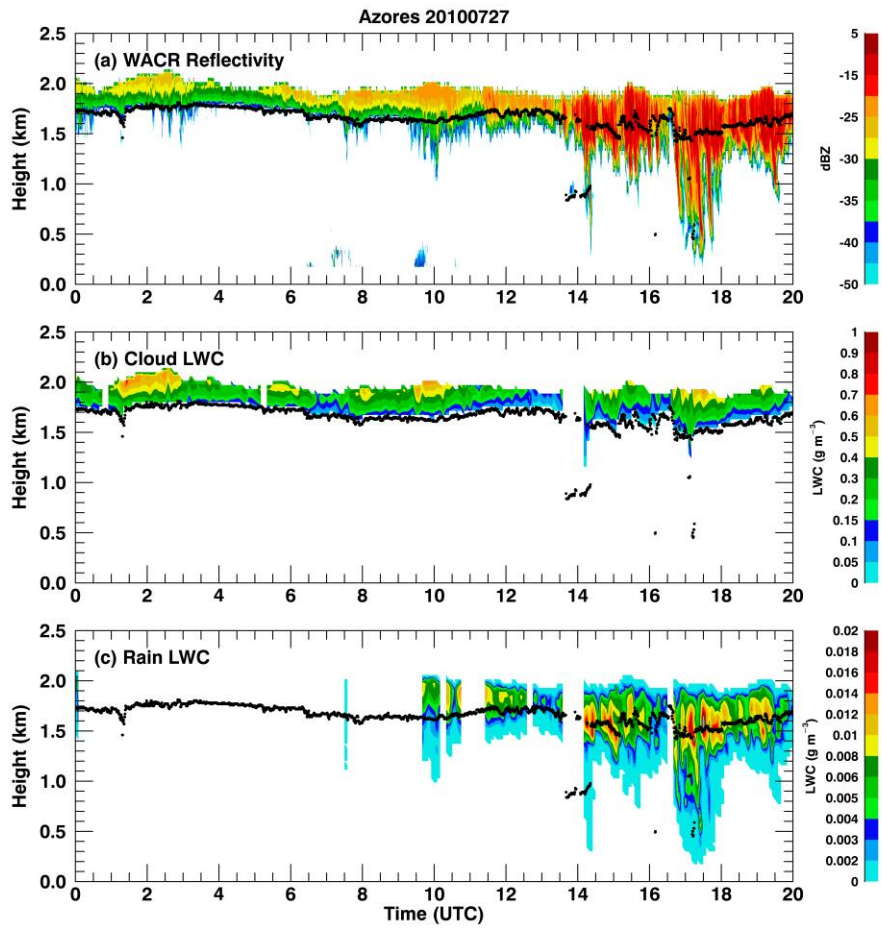

Figure A1. Joint retrieval of cloud and rain liquid water content (CLWC and RLWC) for the same case as in Figure 1. (a) WACR reflectivity, (b) CLWC, and (c) RLWC. The black dots represent cloud base height. Blank gaps are due to the data from one or more observations are not available or reliable. For example, the gap before 14 UTC is due to multiple cloud layers are detected whereas we only focus on single layer cloud.