1 Comment 1

1.1 Comment from Referee

From equations (12) and (15), the 0th and the 3rd moments of DSD are used to estimate Dm in this study. However, it is questionable whether JWD can accurately measure the 0th moment (number concentration of raindrops). The dead time problem and the cut-off at 0.3mm are the reasons for this. According to equation (12), underestimation of the number concentration of raindrops by JWD leads to underestimation of , which in turn leads to overestimation of Dm. It can therefore be assumed that the difference in Dm between the JWD and the simulation is due to errors in the JWD measurement. The DSDs from JWD should be corrected, for example, using the method of Raupach et al. (2019).

1.2 Author's response

Thank you for your comment. In response, we have conducted an analysis to assess the impact of truncation on the mass-weighted mean diameter (D_m). Our approach follows the CASIM particle size distribution (PSD) framework, where D_m is derived as the ratio of the 4th and 3rd moments. By utilizing the regularized incomplete gamma function, we quantify the truncation effect at D_{cut}, corresponding to the lowest size detected by JWD. The results indicate that while individual moments are affected by truncation, their ratio remains largely unchanged. Since our histograms of D_m already start above 0.5 mm, the bias introduced by truncation is minimal, and hence the shape parameter (μ) remains unaffected or realistic. These findings suggest that discrepancies between JWD and model-derived D_m are negligible due to truncation and the analysis discussed in the manuscript remain valid.

The CASIM particle size distribution definition is

$$N(D) = N\frac{\lambda^{1+\mu}}{\Gamma(1+\mu)}D^{\mu}\exp(-\lambda D) \tag{1}$$

where N is the total number concentration and λ, μ are PSD parameters.

The p-th moment of this distribution is given by

$$M(p) = \frac{N\Gamma(1+\mu+p)}{\lambda^{p}\Gamma(1+\mu)} \tag{2}$$

The mass-weighted mean size is given by the ratio of the 4th and 3rd moments for liquid droplets:

$$D_m = \frac{M(4)}{M(3)} \tag{3}$$

We will use the regularized incomplete upper gamma function (`scipy.special.gammaincc`) from the Python `scipy.stats` library to estimate the moments used to compute the mass-weighted mean diameter D_m, assuming that μ is fixed and the same for both truncated and full distributions.

$$Q(a,x) = \frac{1}{\Gamma(a)}\int_{x}^{\infty} t^{a-1}\exp(-t)\mathrm{d}t \tag{4}$$

such that $Q = 1$ when $x = 0$.

For the CASIM PSD, we define $t = \lambda D$, $a = \mu + 1 + p$ where p is the p-th moment ($p = 0$: number concentration, $p = 3$: mass concentration). The truncation is applied at $x = \lambda D_{\mathrm{cut}}$, where D_{cut} is the lowest size observed by the JWD sensor.

To estimate the ratio of JWD-derived $D_{m,\mathrm{jwd}}$ to CASIM $D_{m,\mathrm{mod}}$:

$$\frac{D_{m,\mathrm{jwd}}}{D_{m,\mathrm{mod}}} = \frac{Q(1+\mu+4, \lambda D_{\mathrm{cut}})}{Q(1+\mu+3, \lambda D_{\mathrm{cut}})} \tag{5}$$

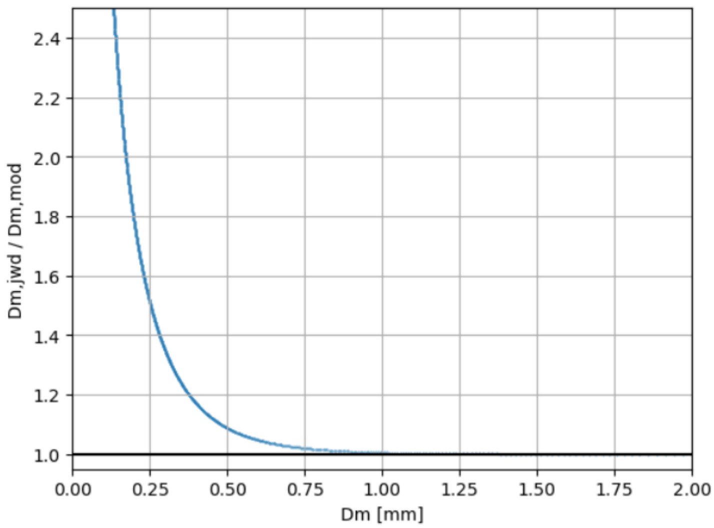

Figure 1: Scatter plot showing the ratio of JWD-derived mass-weighted mean diameter (D_m,jwd) to the CASIM model-derived mass-weighted mean diameter (D_m,mod) as a function of D_m(in mm)

The analysis shows that the effect of truncation on the mass-weighted mean diameter (D_m) is minimal because both the third and fourth moments are truncated at similar rates. As a result, their ratio remains largely unchanged. While truncation significantly affects individual moments, their proportionality ensures that D_m is stable.

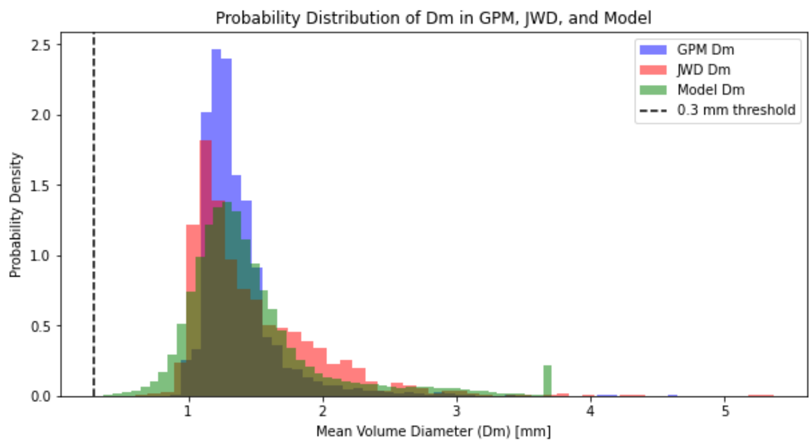

Figure 2: Histogram showing the probability density of drops in D_m size range

Given that the histograms of D_m already start at $D_m \approx 0.5$ mm, this confirms that truncation does not introduce any valid bias. Consequently, since D_m remains unaffected, the shape parameter (μ) is also unlikely to be impacted. Thus, truncation does not concern the validity of the results. Furthermore, because the truncation has less than a 5% effect on $D_m > 0.75$ mm, we can assert that μ should also remain unaffected.

1.3 Author's changes in manuscript

Since the authors explanation validate the methods used in the study, there is no related changes based on this comment in the manusript.

2 Comment 2

2.1 Comment from Referee

P12 Lines 267-269: The authors state that "the model shows agreement with the JWD and GPM for raindrops with a maximum frequency of occurrence of Dm between 1 mm and 2 mm", but the model seems to overestimate Nw compared to the JWD. It is desirable to have a quantitative comparison between the simulation and the observation.

2.2 Author's response

Thank you for your insightful comment. To address your concern, we conducted a probability density analysis, which confirmed that the maximum probability of occurrence for D_m in GPM, JWD, and the model lies between 1 mm and 2 mm, as stated in the manuscript.

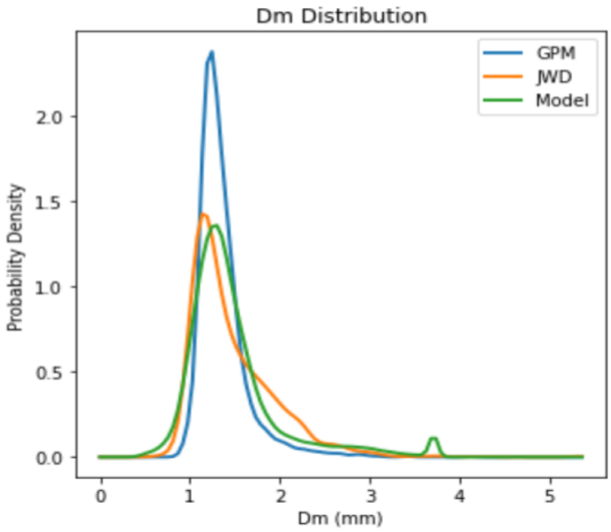

Figure 3: Histogram showing the probability density of drops in D_m size range

Additionally, we performed a quantitative bias analysis to assess the differences between the simulation and observations.

For D_m, the mean bias error (MBE) indicates that GPM (-0.1131) and model (-0.0112)underestimates D_m , relative to JWD . The mean absolute error (MAE) and root mean square error (RMSE) suggest moderate error spreads, with the model having a larger RMSE (0.7033) than GPM (0.5531).

For N_w, the bias analysis shows that GPM significantly underestimates N_w(MBE = -968.91), whereas the model overestimates it (MBE = 1877.85). The high RMSE values for both GPM and the model (6013.88) suggest considerable variation in N_w predictions.

The current study focuses on assessing the underestimation of larger raindrops, which, despite their lower number density, play a crucial role as they are typically associated with convective rainfall. Since convective processes contribute significantly to precipitation intensity and accumulation, understanding biases in larger drop representations is essential for improving model performance and precipitation estimates.

2.3 Author's changes in manuscript

The result of the quantitative bias analysis is added to the manuscript to the manuscript.

3 Comment 3

3.1 Comment from Referee

Equation (8): 103 should be in the numerator because the unit of LWC is [g/m3] and the unit of w is [kg/m3].

3.2 Author's response

Thank you for your comment. The discrepancy arises due to the unit system used in our derivation. We expressed ρ_w in g/cm$^{\mathbf{3}}$ instead of kg/m$^{\mathbf{3}}$, which eliminates the need for the factor 10^3 in the numerator. However, we acknowledge that we did not explicitly mention the unit conversion in the derivation, which may have caused the confusion. We will clarify this in the revised manuscript to ensure consistency in unit representation.

3.3 Author's changes in manuscript

The unit is specified explicitly on the manuscript.

4 Comment 4

4.1 Comment from Referee

Fig. 7c: The plots for convective precipitation are not visible due to overlap.

4.2 Author's response

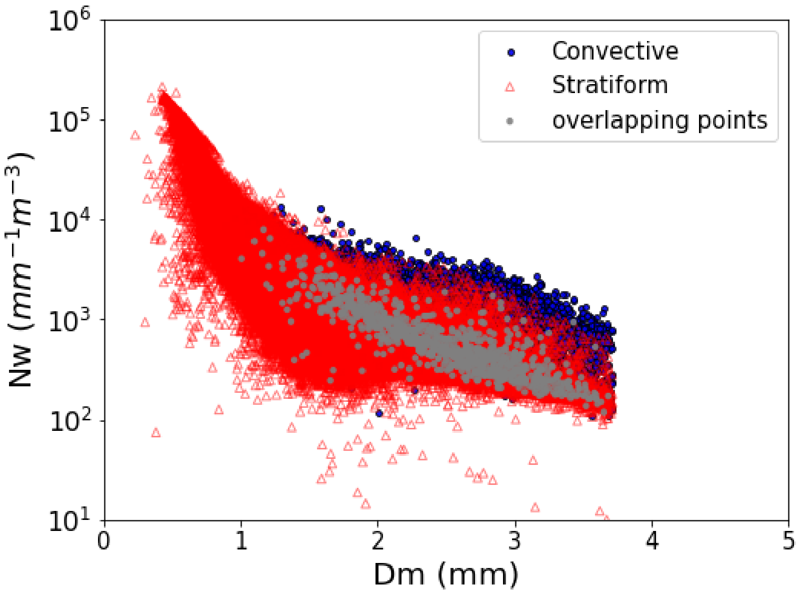

Figure 4: The DSD distribution shows convective and stratiform drops and the overlapped points show the presence of both convective and stratiform drops in the region.

Thank you for your valuable feedback. We acknowledge that the overlapping points in Figure (c) are not visible. Since GPM and JWD have minimal overlap in drop size distributions, we applied the same pattern to the model for consistency in comparison. However, as you rightly pointed out, to improve visualization, a revised figure is provided below where the overlapping points are more clearly distinguishable.

4.3 Author's changes in manuscript

The figure to visualise the overlapping points is added to the manuscript.

Comments from referee

There is a basic concept error about autoconversion process. The authors state that "The autoconversion process is a primary microphysical process in which the cloud droplets collect the raindrops to form a bigger drop." This is totally wrong. According to glossary of meteorology from AMS, autoconversion means "The initial stage of the collision–coalescence process whereby cloud droplets collide and coalesce to form drizzle drops". This process doesnot directly produce big raindrop at all.

Author's response

We sincerely thank the reviewer for pointing out the misstatement regarding the autoconversion process. Upon review, we acknowledge that our original statement was incorrect and does not align with the widely accepted definition provided by the AMS Glossary of Meteorology.

While autoconversion is not a discrete process observed in the real-world continuum of collision-coalescence, it is a conceptual parameterization used in bulk microphysical models. In these models, autoconversion represents the flux of mass and number across a size threshold, which separates the cloud water from rainwater species. Specifically, the parameterization simulates the coalescence of small cloud droplets into drizzle or rain-sized particles, facilitating the conversion of cloud water species into rainwater species. Beyond this threshold, processes such as self-collection within the rain species further increase the mean size of raindrops.

Implications for our Study:

- Autoconversion remains an essential process to test and evaluate in microphysical schemes, as it plays a critical role in the partitioning of water species and impacts precipitation characteristics in bulk models.
- This process, while idealized, allows models to account for the continuum of droplet growth and serves as a proxy for the early stages of the collision-coalescence process
- The evaluation and sensitivity experiments conducted in this study were not intended to enhance the growth of raindrops but rather to assess how a more advanced parameterization impacts the representation of the drop size distribution (DSD) compared to the existing approach.

Author's changes in manuscript

The authors revised the text in our manuscript as follows to accurately reflect the concept ; "In bulk microphysical models, the autoconversion process is a parameterized mechanism that simulates the transition of cloud water species to rainwater species due to the coalescence of cloud droplets. It represents the flux of mass and number across a size threshold, distinguishing clouds from rain particles. While this process is an idealization, it is crucial for modeling precipitation and requires careful evaluation."

Comments from referee

The comparison of DSD parameters from JWD, DPR, and NCUM-R after stratiform-convective separation is even not an apple-to-apple comparison. Three separation algorithms are based on different criteria and physical concept. The same criteria should be used, such as a simple reflectivity threshold of 35 dBZ.

Author's response

We acknowledge the concern raised by the reviewer about the ‘apple to apple’ comparability of stratiform and convective separation criteria used in different datasets. While using the uniform reflectivity threshold might provide consistency, at the same time, it overlooks the unique strengths and limitations of each dataset.

1) JWD data lacks a direct calculation of reflectivity measurements; it relies on the rain rate and drop size to obtain reflectivity. So, using rain rate thresholds which is a derived parameter used to classify stratiform and convective rain, is more meaningful and sensible.

2) GPM-DPR, which has radar-based reliable capabilities, uses multiple criteria using both the presence of a bright band and the horizontal method, both evaluate the reflectivity thresholds across the vertical profiles and horizontal gradients, which is not possible to evaluate from JWD as it is a ground observation instrument. (reference: https://doi.org/10.1175/JTECH-D-16-0016.1)

3) NCUM-R is a non-hydrostatic model that uses vertical velocity as a prognostic variable, hence for tropics, it can provide a comprehensive classification of convective and stratiform rain from the embedded convective system. This along with the combined rain rate criteria marks a more reliable classification of rain. (Houze Jr, R. A.: Stratiform precipitation in regions of convection: A meteorological paradox? Bulletin of the American Meteorological Society, 78, 2179–2196, 1997.)

In terms of the above-mentioned points, using data-specific separation criteria is relevant in the context of each system as:

- ○ Each dataset has unique capabilities and limitations so using the same criteria (35dBZ) does not promise to fulfill the intention of the study.
- ○ The study tried to use the best possible method for each dataset, as the motive was to more accurately separate the convective and stratiform precipitation, hence evaluating the drop size distribution pattern represented by each dataset and analyzing it further in terms of microphysical processes.
- ○ Recent work by Peinó et al (https://doi.org/10.3390/rs16142594) used data-specific criteria for similar classifications for their objectives.

Author's changes in manuscript

Since the authors explanation validate the methods used in the study, there is no related changes based on this comment in the manusript.

Comments from referee

Figure 7: Within the Dm-Nw framework, the precipitation rate R can be directly calculated for a given shape parameter μ. The differences simply come from the sample error and truncation error, which have no physical meaning.

Author's response

Thank you for your valuable comment. A similar concern was raised by reviewer 1, and in response, we conducted a detailed analysis to assess the impact of truncation on the mass-weighted mean diameter (Dm). Our approach follows the CASIM particle size distribution (PSD) framework, where Dm is derived as the ratio of the fourth and third moments. Using the regularized incomplete gamma function, we quantified the truncation effect at Dcut, which corresponds to the lowest droplet size detected by JWD.

The results indicate that while truncation influences individual moments, their ratio remains largely unchanged. Given that our histograms of Dm already start above 0.5 mm, the bias introduced by truncation is less than 10%. Consequently, the shape parameter (μ) remains unaffected as Dm is realistic, and the discrepancies between JWD and model-derived Dm are not a result of truncation.

Additionally, sample errors in Dm can be related to errors in the precipitation rate (R) within the Dm-Nw framework. However, since Dm is relatively insensitive to truncation and its effect on μ is negligible, the analysis-based Dm remains valid. The detailed derivation is attached.

Author's changes in manuscript

Since the authors explanation validate the methods used in the study, there is no related changes based on this comment in the manusript.