A Possible Use of Multi-Sensor Satellite Observations for Inferring the Drop Collection Efficiency of Warm Clouds

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Abstract

This study proposes a combined use of spaceborne cloud profiling radar, shortwave and microwave measurements provided by the A-Train constellation of satellites to investigate the warm-rain collection process in low clouds. The continuous collection model is employed to interpret the relationship between the observables of CloudSat, MODIS and AMSR-E measurements. The theoretical formula representing the collection process involves the collection efficiency factor, which is then inferred from these observations by exploiting the differing sensitivities of these sensors to cloud drop sizes. The collection efficiency implied ranges from the order of 0.001 to that of 1.0, and is systematically larger than estimated by traditional methods when updraft velocity is ignored in the continuous collection model. The collection efficiency is also found to increase with columnar effective particle radius in a manner consistent with classical relationships. These results suggest that the new observations provide a gross measure of the real collection efficiency factor on the global scale.

1. Introduction

The climatic effects of clouds are influenced by precipitation formation processes that determine the rate at which cloud water falls from the atmosphere. The rain formation in liquid-phase clouds is initiated by the coalescence process, where the rate at which the cloud droplets grow into the rain drops is strongly controlled by the ability of one droplet collecting another droplet. This ability is characterized by the collection efficiency which quantifies the efficiency of the coalescence process. An important character of the collection efficiency is its dependence on particle radius, which controls the pattern and the rate of evolution of the drop size spectra due to the coalescence process (e.g., Berry 1967), and then provides a pathway through which aerosol particles affect the warm rain process.

Many studies reported on the collection efficiency obtained from laboratory experiments (e.g., Beard and Ochs 1984) and numerical simulations (e.g., Pinsky et al. 2000). These previous studies showed how the collection efficiency varies with particle size (e.g., Long 1974) and turbulent flows through aerodynamic effects (e.g., Pinsky et al. 2000). Despite the efforts of these previous studies, the character of the collection efficiency in the real atmosphere, and especially on the global scale, remains largely unknown.

The recent emergence of CloudSat satellite provides the first opportunity to observe vertical structure of clouds on the global scale with the spaceborne Cloud Profiling Radar (CPR) (Stephens et al. 2008). The Cloud

Sat satellite was designed to fly as part of satellite constellation called A-Train that is comprised of satellites with various active and passive sensors, aiming at simultaneous observations of various aspects of cloud-to-precipitation processes. The A-Train includes the Earth Observing System (EOS) Aqua satellite, which is equipped with the MODerate resolution Imaging Spectroradiometer (MODIS) visible/infrared radiometers and the Advanced Microwave Scanning Radiometer for the Earth Observing System (AMSR-E) microwave imager. This paper proposes a synergistic use of these observations to examine the collection process of warm clouds defined by a theoretical relationship between the observables. The differing sensitivities of these sensors to particle sizes are exploited to construct the relationship and then to provide an implication for the collection efficiency that is inferred from these observations.

2. The collection process

Cloud droplets grow through the condensation process in air being lifted by upward air motion in the early stage of cloud development, where the particle size tends to increase with height. When the particles become large enough to collide with each other, the collision-coalescence process begins and particles then fall downward and grow by collecting the cloud water.

The most sophisticated and realistic representation of the collision-coalescence process is provided by the stochastic collection equation that describes the evolution of a cloud droplet size distribution. Although the stochastic aspect of cloud particle growth to rain drops is important, many basic characteristics of the process can be represented in a simpler manner by the continuous growth model, which assumes that all large drops of the same size grow at the same continuous rate (e.g., Pruppacher and Klett 1997). Although this continuous collection model has recognized limitations, its simplicity provides a convenient basis for analyzing the new A-Train observations.

The continuous model describes how a collector drop of mass of M (and radius of R) grows by falling through and sweeping out the population of smaller cloud particles of mass of m (and radius of r) distributed according to the size spectra $n(r)$. The growth rate of $M(R)$ is written as

$$\frac{dM}{dt} = \int E_c(R, r) \pi (R + r)^2 (V(R) - V(r)) n(r) m(r) dr, \quad (1)$$

where E_c and V denote the collection efficiency and terminal fall velocity, respectively. Assuming that the collector drop is larger than the collected droplets, (1) can be approximated as (e.g., Rogers and Yau 1989)

$$\frac{dM}{dt} = E_c \pi R^2 V(R) q_c, \quad (2)$$

where $q_c = \int n(r) m(r) dr$ is cloud water content (in gm^{-3}). Recalling $dM = \rho_w 4\pi R^2 dR$, (2) leads to an expression of growth rate in terms of radius R as

$$\frac{dR}{dt} = \frac{E_c V(R)}{4\rho_w} q_c, \quad (3)$$

where ρ_w denotes the liquid water density. By neglecting the upward air velocity as much smaller than the fall velocity $V(R)$, then (3) can be transformed into the growth rate with regard to height h as (e.g., Rogers and Yau 1989)

$$\frac{dR}{dh} = \frac{dR}{dt} \frac{dt}{dh} = -\frac{dR}{dt} \frac{1}{V(R)} = -\frac{E_c}{4\rho_w} q_c. \quad (4)$$

The negative sign means that the particle radius R increases downward.

Vertical integration of (4) leads to an expression for the change in particle radius ΔR through the cloud layer as

$$\Delta R = \frac{\bar{E}_c}{4\rho_w} W, \quad (5)$$

where $W = \int_{top}^{base} q_c dh$ is liquid water path of the collected cloud droplets (in gm^{-2}), and $\bar{E}_c$ is the vertically averaged non-dimensional collection efficiency factor.

3. Analysis approach

Under the assumption of continuous collection, every collector drop is considered to grow at same rate based on a mono-disperse size distribution function, and thus the change in radar reflectivity Z_e is simply given as

$$\frac{dZ_e}{Z_e} = 6 \frac{dR}{R}. \quad (6)$$

ΔR can therefore be approximated by the change in Z_e through the cloud layer as

$$\Delta R \approx \frac{\bar{R}}{6} \Delta \ln Z_e, \quad (7)$$

where $\bar{R}$ is the vertically averaged particle radius. Combining (5) and (7), we obtain

$$\Delta \ln Z_e \approx \frac{3}{2} \frac{\bar{E}_c}{\rho_w \bar{R}} W. \quad (8)$$

The relationship (8) interprets the vertical change in radar reflectivity Z_e (typically increasing downward for drizzling clouds) through the cloud layer as induced by the continuous collection of cloud droplets represented by W and $\bar{R}$, involving the collection efficiency $\bar{E}_c$ as a parameter. We examine the relationship (8) using the A-Train-based estimates for W , $\bar{R}$ and Z_e .

The cloud water path W of the collected droplet can be estimated from MODIS cloud product of effective particle radius r_e and optical thickness τ_c (e.g., Platnick et al. 2003) following the formula of Stephens (1978) as

$$W = \frac{3}{2} \rho_w r_e \tau_c.$$

The MODIS analysis provides a reasonable estimate of cloud water path that does not include drizzle particles since the shortwave retrieval yields particle size near the cloud top (Nakajima and King 1990) where drizzle particles are not likely to exist. The MODIS-derived cloud top temperature T_c is also used for restricting the analysis to warm clouds identified as those with T_c higher than 273.15 K. The clouds with $\tau_c < 3$ are also screened out from current analysis to avoid non-drizzling thin clouds.

An estimate of $\bar{R}$ is obtained using the method of Masunaga et al. (2002) that combines the microwave-derived liquid water path W_{mw} with the shortwave-retrieved optical thickness τ_c to compute the columnar

effective radius $R_{e,column}$ as

$$R_{e,column} = \frac{3}{2} \frac{1}{\rho_w} \frac{W_{mw}}{\tau_c}.$$

We employ W_{mw} derived from AMSR-E observations with the algorithm of Wentz and Spencer (1998) and τ_c obtained from MODIS cloud product (e.g., Platnick et al. 2003) for this purpose. $R_{e,column}$ thus obtained includes a contribution from drizzle-sized particles reflecting the microwave sensitivity (Masunaga et al. 2002) and we use $R_{e,column}$ as an estimate for $\bar{R}$ in (8). To reduce the uncertainty from the difference in horizontal resolution between the shortwave and microwave measurements, we analyze the data with cloud fractions larger than 0.9 obtained from MODIS 5 km products matched to CloudSat footprint. Although this procedure may not be a complete correction for the beam-filling problems, the present analysis would not cause serious errors for our climatological interest in warm clouds (e.g., stratocumulus and stratus) that extend over wider scale with relatively homogeneous features. Since the microwave retrieval of the liquid water path is limited to ocean areas, the present analysis is restricted to the global ocean.

The vertical change in radar reflectivity is obtained from CloudSat 2B-GEOPROF product (e.g., Mace et al. 2007). For drizzling clouds subject to collection processes, the reflectivity profile typically has a minimum value Z_{min} near the cloud top and the maximum value Z_{max} in lower levels just above the lowest layer where Z_e decreases downward mainly due to attenuation. For selecting the reflectivity profiles of this type, we apply the least square fitting of linear function to each reflectivity profile and find the profiles of negative slopes. We further choose the single-layered cloud profiles with thicknesses exceeding 1000 m. The reflectivity change through the cloud layer is then estimated for these profiles as

$$\Delta \ln Z_e = \ln \left(\frac{Z_{max}}{Z_{min}} \right).$$

Since the CloudSat-observed radar reflectivity has an accuracy of about 2 dBZ as determined by radiometric calibration (Tanelli et al. 2008), the uncertainty of $\Delta \ln Z_e$ is estimated as 4 dBZ, leading to a possible error of collection efficiency ranging from 0.01 to 0.1 given the range of $W/(\rho_w \bar{R})$ as from 5 to 40 as shown in Fig. 1.

4. Collection efficiency

Figure 1 shows the joint probability distribution function (JPDF) between $\Delta \ln Z_e$ and $W/(\rho_w \bar{R})$ obtained for 2007 June-July-August (JJA) season over the ocean of 60°S–60°N. The slope between these two quantities relates to the collection efficiency $\bar{E}_c$ as shown by dashed lines representing the theoretical relationship (8) for specified values of $\bar{E}_c$. The comparison of the observed JPDF and the theoretical lines suggests that the theoretical relationship given from the continuous collection model can be used to interpret the A-Train-observed parameters as suggests a diversity of collection efficiency values ranging approximately from 0.03 to 3.0.

The values of $\bar{E}_c$ implied from this comparison are shown as a solid curve of the probability distribution function in Fig. 2. The figure illustrates that the collection efficiency tends to range from about 0.003 to 10.0 with the most frequent value of about 0.3. It is found that a considerable portion of the population belongs to the physically unrealistic range of $\bar{E}_c > 1.0$, which suggests that the inferred collection efficiencies are

Fig. 1. Joint probability distribution function between $\Delta \ln Z_e$ (in dBZ) obtained from CloudSat and $W/(R\rho_w)$ (no dimension) obtained from combined MODIS and AMSR-E analysis (see text for details) for maritime area of 60°S–60°N during 2007JJA. Theoretical relationship (8) is also shown for reference as dashed lines for specified values of collection efficiency $\bar{E}_c$ as labeled.

likely biased to larger values.

A possible cause for this overestimation may be the neglect of the updraft velocity w , which may lead to smaller values of collection efficiency although its effect is not clear in turbulent states as discussed in Section 5. When the air velocity w (taken positive for upward) is not negligible compared to the terminal fall velocity $V_t = V(R)$ (taken positive for downward), (8) is extended to a more general form as

$$\Delta \ln Z_e = \frac{3}{2} \bar{E}_c \frac{W}{\rho_w R}, \quad \bar{E}_c = \frac{\bar{E}_c}{1 - w/V_t}. \quad (9)$$

(9) means that the apparent collection efficiency $\hat{E}_c$ inferred from the present method is influenced by air velocity w through its relative magnitude to terminal velocity V_t . When w is comparable to V_t , the pure collection efficiency $\bar{E}_c$ becomes smaller than $\hat{E}_c$, and may then be less subject to the overestimation found above.

To quantitatively examine the effects of updraft velocity on inferred values of collection efficiency, we also show in Fig. 2 the estimates of $\bar{E}_c$ inferred with the assumed values of w/V_t . The values of $\bar{E}_c$ are found to become systematically smaller for larger values of w/V_t , making the $\bar{E}_c$ values more reasonable. This implies that the particle growth pattern represented by the vertical profile of radar reflectivity is significantly influenced by updraft velocity. Despite these sources of uncertainty, the majority of the estimated $\bar{E}_c$ broadly lies in the reasonable range of $0.003 < \bar{E}_c < 1.0$, and we interpret the implied values of $\bar{E}_c$ to be a gross index of the real collection efficiency.

For examining the behavior of the inferred collection efficiency, it is important to investigate how the $\bar{E}_c$ values relate to particle radius. Figure 3 shows the inferred values of $\bar{E}_c$ for specified values of w/V_t as a function of columnar effective particle radius $R_{e, \text{column}}$, taken to be a proxy for collector drop radius. The figure shows the averaged values and the standard deviations of $\bar{E}_c$ computed for each bin of $R_{e, \text{column}}$ as central points and vertical bars, respectively. Also shown in Fig. 3 are the classical relationships of Long (1974) given as

$$E_c = \begin{cases} k_1 R^2 (1 - k_2/r) & (R < 50 \text{ } \mu\text{m}) \\ 1 & (R \geq 50 \text{ } \mu\text{m}) \end{cases},$$

where $k_1 = 4.5 \times 10^4 \text{ cm}^{-2}$ and $k_2 = 3 \times 10^{-4} \text{ cm}$ (Long 1974), and the radius of collected droplet r is assumed to be 10 μm and 20 μm .

Fig. 2. Probability distribution function of the collection efficiency $\bar{E}_c$ inferred from A-Train observations for specified values of w/V_t according to (9).

Fig. 3. Scatter plot of the collection efficiency as a function of columnar effective particle radius obtained from A-Train observations for specified values of w/V_t in comparison with classical relationship suggested by Long (1974).

It is demonstrated in Fig. 3 that the A-Train-inferred $\bar{E}_c$ tends to increase with increasing $R_{e, \text{column}}$ in broad agreement with Long's relationship despite the discrepancy in absolute values of $\bar{E}_c$, which become larger for smaller values of w/V_t . The observed relationship is approximated as $\bar{E}_c \propto R_{e, \text{column}}^{1.7}$ based on the least square fit to the plot, which is slightly different from $E_c \propto R^2$ suggested by Long (1974) for $R < 50 \text{ } \mu\text{m}$.

5. Possible errors

The results shown above demonstrate the applicability of the present approach to the A-Train observations for examining a basic aspect of the collection process. There remains, however, several issues that may cause possible errors associated with the present formulation based on the continuous collection model and a simple representation of air velocity effects.

We employed $R_{e, \text{column}}$ as an estimate for $\bar{R}$ that is introduced as a collector drop radius and then should typically reach as large as 100 μm although $R_{e, \text{column}}$ tends to stay in range smaller than this value. When this discrepancy between $R_{e, \text{column}}$ and $\bar{R}$ is taken into account, the inferred values of collection efficiency tend to become larger and to provide further overestimates of $\bar{E}_c$. This implies an inherent behavior of the present formulation that tends to provide systematically larger

values of collection efficiency. This is expected given the nature of the continuous collection model used to interpret the data as this model requires substantially longer times than observed to form precipitation-sized particles due to a neglect of the stochastic aspect of the collection process (e.g., Telford 1955). The slower particle growth inherent in the continuous model is compensated by larger values of the collection efficiency to match the observed values of the cloud properties.

The continuous collection model also imposes the assumption of constant number concentration of collector drops, which relates the changes in Z_e with those in R through sixth power as shown in (6). In the real atmosphere, however, the collector drops are likely to increase in number as the coalescence process proceeds and then Z_e may relate to R with a power larger than six. This effect tends to reduce the overestimate of collection efficiency values. It would be necessary in future studies to take the stochastic behavior of the collection process into account for improving these issues. The stochastic nature also tends to provide broader size spectra rather than the mono-disperse function induced by the continuous model.

Although the effects of updraft velocity are examined in a simple way within the present framework, the vertical motions in real clouds are complex with a mixtures of upward and downward air motions on all sorts of varying scales. For low stratiform clouds, the scale of updrafts and downdrafts are typically smaller than the footprint of the radar (1.7 km) and thus we expect that the effects of motion might be somewhat averaged out. It is difficult to examine the effects of air motions in more detail at this time without available observations of them on the global scale. In this regard, it is worth noting that recent studies have started to retrieve the air velocity from ground-based Doppler CPR (e.g., Sato et al. 2009), which would provide a future opportunity of exploring how the air velocity influences the collection process.

6. Conclusion

This study introduces an approach to examine the cloud drop collection process in low-level clouds based on multi-sensor observations with CloudSat CPR, MODIS shortwave and AMSR-E microwave measurements. The differing sensitivities of these sensors to particle size changes are exploited in a theoretical relationship that connects the observables to the continuous collection process. The CloudSat-observed profiles of the radar reflectivity are combined with the MODIS-derived liquid water path taken to be representative of smaller droplets and the column mean particle radius as introduced by Masunaga et al. (2002). A relationship between these observed quantities and the collection efficiency is developed and the collection efficiency $\bar{E}_c$ is estimated using this relationship. This efficiency is found to range between about 0.003 and 10.0 with a considerable portion of $\bar{E}_c > 1$, likely suggesting an overestimate possibly due to the neglect of the stochastic aspect of collection process and also due to the neglect of updraft velocity in the continuous model. It is demonstrated that the inferred collection efficiency tends to vary with particle radius in a manner similar to theoretical relationships, suggesting that the inferred collection efficiency reflects the behavior of the real collection efficiency factor.

The approach described in this paper provides a means for inferring the collection efficiency of warm clouds on a global scale. Although the approach introduced is novel and lacks maturity, it offers a first step to

quantitatively examine the behavior of the collection process of liquid clouds as a function of environmental factors (like aerosols and stabilities) using the real-world's observational data. This method will be applied to surface observations that are analogous to the A-Train observations employed in this study but with added vertical motion capability to address the uncertainties of the approach.

Acknowledgments

The CloudSat, AMSR-E and MODIS products were provided by CloudSat Data Processing Center, National Snow and Ice Data Center and NASA/GSFC, respectively. We are grateful to John Haynes and Philip Partain who handled these data through A-Train Data Depot. This study was supported by NASA grant #NNX07AR11G.

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