

Article

Cross-Platform Comparison of Marine Boundary Layer Cloud and Drizzle Properties over the Southern Ocean Using Airborne, Shipborne, and Satellite Observations

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Highlights

Cloud and drizzle properties in Southern Ocean (SO) marine boundary layer clouds were examined using aircraft, shipborne, and satellite observations to compare how different observational platforms detect and characterize the similar cloud regimes sampled over the same SO region during the austral summer season.

What are the main findings?

- Consistent cloud–drizzle retrievals across platforms. The reflectivity–retrieval framework provides consistent macrophysical and microphysical properties of liquid-dominant SO MBL clouds and drizzle from airborne (SOCRATES), ship-based (MARCUS), and satellite (CloudSat) observations.
- Retrieved cloud structures are physically realistic, while instrumental limitations explain most differences. The retrieved vertical distributions of cloud and drizzle properties are consistent with the dominant physical growth processes. Differences among the three platforms reflect variations in radar sensitivity, vertical resolution, and sampling strategy.

What are the implications of the main findings?

- Toward unified cloud–drizzle retrievals. A single in situ-derived reflectivity–microphysics framework can be applied across airborne, ship-based, and satellite radars, enabling more coherent multi-platform cloud and drizzle climatologies.
- Stronger confidence in MBL cloud process interpretation. The retrieved cloud–drizzle structures across platforms support robust physical interpretations of SO MBL clouds and provide a benchmark for improving retrievals and climate model evaluation.

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Abstract

Marine boundary layer (MBL) clouds strongly influence radiation and precipitation over the Southern Ocean (SO), yet their vertical structures and microphysical properties remain poorly constrained across observational platforms. This study compares macrophysical and microphysical properties of single-layer, liquid-dominant MBL clouds below 3 km using aircraft observations from the SO Clouds, Radiation, Aerosol Transport Experimental Study (SOCRATES), ship-based observations from Measurements of Aerosols, Radiation, and Clouds over the SO (MARCUS), and satellite observations from CloudSat. An empirical reflectivity–microphysics retrieval framework developed from in situ droplet size distributions (DSDs) measured during SOCRATES was applied to MAR-

CUS M-WACR and CloudSat CPR reflectivity observations to retrieve vertical profiles of number concentration (N), effective radius (r_e), and liquid water content (LWC) for cloud and drizzle particles. Cloud boundary heights and retrieved microphysical properties show broad agreement across the three platforms within the limitations imposed by instrumental sensitivity, sampling differences, and retrieval uncertainties. However, CloudSat CPR observations exhibit larger deviations because of their coarser vertical resolution and lower reflectivity sensitivity, including limited detection of low clouds below ~500 m. The observed vertical structures are consistent with condensational growth, entrainment, and collision–coalescence processes. Overall, the results demonstrate broad consistency in cloud and drizzle properties across the three platforms, while highlighting the impacts of instrumental sensitivity, vertical resolution, and sampling differences on cloud boundary detection and microphysical retrievals.

Keywords: MBL cloud and drizzle macro- and microphysical properties over the SO; in situ measurements; radar observations; SOCRATES airborne campaign; MARCUS ship-based campaign; CloudSat satellite observation

1. Introduction

Marine boundary layer (MBL) stratocumulus clouds are prevalent over the Southern Ocean (SO), where they play a critical role in reflecting solar radiation and regulating the surface energy budget [1–4]. These clouds frequently contain substantial supercooled liquid water (SLW; [5]) and exhibit microphysical characteristics distinct from both subtropical MBL liquid clouds [6,7] and Arctic mixed-phase clouds with liquid-over-ice structures [8,9]. Despite their importance to Earth’s radiation budget, global climate models (GCMs) continue to exhibit large biases in simulating SO MBL clouds, including underestimation of cloud fraction and SLW, as well as overestimation of cloud brightness and light precipitation [10,11]. Improving our understanding of the vertical structure and microphysical properties of SO MBL clouds is therefore essential for advancing cloud parameterizations and reducing climate-model uncertainties.

Determining the distributions and vertical profiles of cloud and drizzle microphysical properties in MBL clouds is essential for understanding cloud growth and cloud-to-rain conversion processes. MBL cloud droplets grow by condensation from cloud base to top, transition to drizzle-size drops through collision–coalescence near the cloud top and then fall while continuing to grow by collecting cloud droplets and small drizzle drops (e.g., [12,13]). High-temporal-resolution in situ observations are therefore critical for accurately retrieving cloud and drizzle microphysical properties, as well as cloud-to-drizzle transition processes, and for improving our understanding of MBL cloud evolution.

To investigate cloud and drizzle microphysical properties over SO, we utilize observations from three complementary platforms. The first is the NASA CloudSat satellite which carries the 94 GHz nadir-looking Cloud Profiling Radar (CPR). CloudSat has substantially advanced global observations of clouds and precipitation, providing critical benchmarks for passive satellite retrievals and climate-model evaluation [2,3,14–18]. The second is the MARCUS (Measurement of Aerosols, Radiation, and Clouds over the Southern Ocean) campaign, conducted from October 2017 to March 2018. MARCUS deployed the Department of Energy (DOE) Atmospheric Radiation Measurement (ARM) Mobile Facility (AMF2) aboard the Australian icebreaker Aurora Australis [19–22]. This ship-based campaign provided high-quality surface-based measurements of SO MBL clouds using instruments including the zenith-pointing 94 GHz Marine W-band ARM cloud radar (M-WACR), microwave radiometer (MWR), Micropulse lidar (MPL) and ceilometer.

The third platform is the SOCRATES (Southern Ocean Clouds, Radiation, Aerosol Transport Experimental Study) aircraft campaign, conducted from 15 January to 26 February 2018 [19,23]. SOCRATES deployed in situ cloud and drizzle probes, including the Cloud Droplet Probe (CDP) and two-Dimensional Stereo Particle Imaging Probe (2D-S), together with remote sensors, such as 94.4 GHz (W-band) HIAPER Cloud Radar (HCR) and 532 nm High Spectra Resolution Lidar (HSRL), aboard the NSF/NCAR Gulfstream-V (GV) aircraft. These measurements provided detailed observations of cloud and drizzle microphysical properties and their vertical structures.

Previous studies have investigated SO cloud vertical structure and microphysical properties using observations from the MARCUS campaign (e.g., [19–22,24,25]) and the SOCRATES field campaigns (e.g., [23,26–29]). Meanwhile, most CloudSat-based studies have primarily focused on global cloud and drizzle characteristics (e.g., [30,31]) or SO precipitation characteristics (e.g., [32]), with limited emphasis on detailed SO boundary-layer cloud and drizzle microphysical structure. Existing retrieval methods have improved understanding of cloud and drizzle microphysics, but most studies examine either cloud or drizzle separately because simultaneously retrieving both in MBL clouds remains challenging. In addition, retrieval algorithms developed for one region or platform are often not directly transferable to other environments due to differences in cloud regimes and microphysical characteristics, highlighting the importance of in situ observations for developing regime-specific retrieval relationships.

Combining satellite, ship-based, and aircraft observations provides a more complete understanding of SO cloud structure and microphysics because each platform offers complementary strengths and limitations [33]. Ship-based radar–lidar systems provide continuous, high-temporal-resolution measurements of the lower atmosphere, aircraft observations offer detailed in situ vertical profiles, and CloudSat provides broad spatial coverage through orbital cross sections [16]. However, differences in sampling, spatial coverage, instrument sensitivity, and vertical resolution complicate direct comparisons among platforms. Integrating these observations enables cross-validation and a more comprehensive characterization of SO MBL cloud and drizzle properties.

The goal of this study is to investigate and compare cloud and drizzle microphysical property retrievals for MBL clouds below 3 km over the Southern Ocean using airborne in situ measurements from SOCRATES (CDP and 2D-S), satellite observations from CloudSat (CPR), and ship-based measurements from MARCUS (M-WACR). The retrievals are based on the framework presented in [29] using SOCRATES CDP and 2D-S observations, providing a consistent basis for cross-platform comparison. Together, these complementary observations offer comprehensive insight into the vertical structure and variability of SO cloud and drizzle microphysical properties.

This paper is organized as follows. Section 2 describes the datasets and methodology. Section 3 presents the cross-platform comparison of cloud and drizzle properties, including their macrophysical and microphysical characteristics and retrieval sensitivity. Section 4 discusses the implications of the cross-platform comparisons and retrieval uncertainties. Section 5 summarizes the major findings and conclusions. Appendices A–C provide additional details on the instrumentation used across the three observing platforms, the retrieval methodology, and associated uncertainties. Supplementary sensitivity analyses and comparisons among different retrieval frameworks are presented in Supplementary Figures S1–S5 and Supplementary Tables S1–S4.

2. Observations from Three Platforms and Retrieval Methodology

Figure 1 shows the selected study domain over the SO, spanning 44°S–63°S and 133°E–163°E. Figure 1a displays the flight tracks of the 15 SOCRATES research flights, while Figure 1b presents the MARCUS ship tracks (with the black rectangle enclosing the

selected study domain). CloudSat observations were also constrained to the same latitude–longitude range. The study period corresponds to the SO summer, including SOCRATES measurements from January to February 2018 and MARCUS measurements from November 2017 to March 2018. CloudSat observations were selected over a five-year period spanning November–March from 2015 to 2020. Previous analysis of CloudSat CPR observations over the study domain by [33] showed that cloud fractions for SO MBL clouds remained highly consistent during November–March from 2015 to 2020, indicating limited interannual variability in the sampled cloud population (see Table S2 of [33]). Therefore, the differences in observation periods among the three campaigns are unlikely to introduce significant biases into the analysis. Constraining the datasets by geographic region, season, and tropospheric height ensures greater homogeneity and consistency across the three platforms, enabling more robust comparisons of cloud vertical structure and microphysical properties.

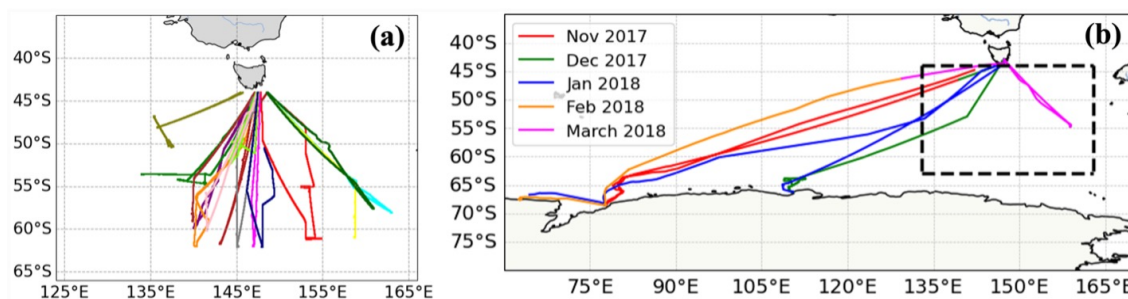


Figure 1. (a) Flight tracks of the 15 research flights from the Southern Ocean Clouds, Radiation, Aerosol Transport Experimental Study (SOCRATES), based in Hobart, Tasmania, during January–February 2018. (b) Ship tracks from the Measurement of Aerosols, Radiation, and Clouds over the Southern Ocean (MARCUS), with the US DOE ARM AMF2 deployed aboard the Australian ice-breaker *Aurora Australis* from November 2017 to March 2018. The shaded region (rectangle with dashed lines) in panel (b) indicates the study domain, where overlapping ship-based, aircraft, and NASA CloudSat satellite measurements were obtained.

All instruments and measurements from the three observational platforms used in this study, together with their sensitivities and uncertainties, are described in Appendix A and summarized in Table A1. Radar reflectivity measurements from the M-WACR, along with cloud base and top heights derived from the ceilometer and MPL [21,34–36], were analyzed together with CloudSat CPR reflectivity measurements [16]. Valid cloud profiles were identified following [33], with cloud occurrence defined by radar returns exceeding the minimum detectable reflectivity (MDR): -50 dBZ for M-WACR and -26 dBZ for CPR; together with the corresponding hydrometeor masks and quality flags provided in each respective dataset. Additional details regarding the cloud detection comparisons and cloud masks across the platforms are provided in [33].

Although CPR reflectivity measurements are well calibrated [17], they remain subject to limitations associated with surface clutter, attenuation, and reduced sensitivity, particularly for low-level MBL clouds. Because the CPR pulse length is approximately 480 m, near-surface ocean reflections contaminate signals below ~ 1 km [17], with no reliable cloud detection below 500 m. Signal attenuation can also become significant in clouds with high LWC, especially within stratocumulus and shallow or deep convection, where radar signals are weakened or absorbed along extended propagation paths. Despite these known limitations, relatively few studies have quantified their impacts on data quality and sampling completeness.

Airborne in situ measurements from the CDP [37–39] and 2D-S probe [40–43] were collected during the SOCRATES campaign, providing detailed observations of cloud and drizzle microphysical properties over the SO. The 2D-S probe further enables discrimination of liquid cloud droplets and drizzle particles, with reliable detection of liquid particles above 40 μm and ice particles above 200 μm [28,42]. These in situ measurements provide the observational basis for developing empirical relationships used to retrieve cloud and drizzle microphysical properties from ground-based MARCUS M-WACR and satellite-based CloudSat CPR radar observations for low-level MBL clouds (<3 km).

2.1. Airborne In Situ Probe-Based Retrieval Method for Cloud and Drizzle Microphysics

The retrieval framework used in this study follows the methodology developed in [29], an airborne in situ probe-based approach developed from SOCRATES CDP and 2D-S measurements for low-level MBL clouds with cloud tops below 3 km. Cloud droplet size distributions (DSDs) were characterized from CDP measurements (2–40 μm), while drizzle DSD spectra were represented using 2D-S observations (40–400 μm). In situ cloud reflectivity (Z_c), liquid water content (LWC_c), and effective radius ($r_{e,c}$) profiles derived from the CDP DSDs generally exhibit near-adiabatic growth, increasing from cloud base to cloud top through the condensation process. In contrast, in situ drizzle profiles (Z_d , LWC_d , and $r_{e,d}$) derived from 2D-S spectra typically increase from cloud top to cloud base, reflecting growth by collision–coalescence processes. The subscript c and d denote cloud and drizzle, respectively. In typical MBL liquid clouds, cloud droplets form near the cloud base, grow through condensation as they rise (reaching $r \sim 20 \mu\text{m}$ [44]), and may transition into drizzle-sized drops near the cloud top via collision–coalescence processes [45]. These drizzle drops then descend, collecting cloud droplets and smaller drizzle drops, leading to further growth toward the cloud base [12]. The resulting profiles of in situ cloud and drizzle Z , r_e , and LWC derived from the CDP and 2D-S size distribution measurements are illustrated in Figure A1 of Appendix B (adapted from [29]).

Empirical relationships were derived between reflectivity (Z , in dBZ), r_e , and LWC for cloud and drizzle droplets, expressed as $r_e = A \cdot \exp(0.0384Z)$ and $LWC = B \cdot \exp(0.115Z)$. For cloud droplets, the coefficients are $A = 23.02$ and $B = 2.70$, while for drizzle droplets they are $A = 49.81$ and $B = 0.15$. The empirical coefficients A and B are sensitive to the underlying DSD parameters and number concentrations (N). In particular, parameters σ_x (logarithmic width) and μ (shape parameter) govern the spread of the lognormal and gamma distributions for cloud and drizzle spectra, respectively, while N reflects the dominant microphysical growth processes. Larger μ values denote more uniform drizzle drop sizes typical of mature or well-mixed cloud regimes, whereas smaller μ values correspond to broader spectra associated with active growth or mixed-phase conditions. Similarly, narrow cloud DSDs (small σ_x) arise from uniform condensation, while broader spectra (large σ_x) reflect processes such as collision–coalescence, evaporation, or entrainment that increase spectral variability.

These physically based relationships were applied to MARCUS ship-based and CloudSat satellite observations, providing a consistent framework to compare MBL cloud and drizzle microphysical properties across airborne, shipborne, and satellite platforms. Detailed mathematical derivations, uncertainty analysis, and sensitivity tests are provided in [29] and summarized in Appendix B.

2.2. Retrieval of Cloud and Drizzle Microphysical Profiles from Ship-Based and Satellite Measurements

Cloud and drizzle reflectivity profiles were retrieved from MARCUS M-WACR [34–36] and CloudSat CPR (2B-GEOPROF; [16]) reflectivity measurements, following the method presented in [21,45], as discussed in Appendix C. Only single-layer cloud profiles

below 3 km were selected for analysis. The ARM M-WACR has a reported calibration uncertainty of approximately 2–4 dB and has been reported to exhibit reflectivity values approximately 4–5 dB lower than the well-calibrated CloudSat CPR and SOCRATES HCR [20,21,33,35,46]. However, the exact magnitude of this bias cannot be precisely quantified because of periodic interruptions in the ship-motion correction system [19,21]. A sensitivity analysis accounting for this uncertainty is presented later by perturbing reflectivity values over the ± 2 to ± 6 dB range.

Cloud-top height (H_{top}) was derived from M-WACR with ~ 30 m vertical resolution and ~ 1 dB uncertainty [35], while cloud-base height (H_{base}) was obtained from the Micro-pulse Lidar (MPL) and Vaisala ceilometer with ~ 15 m uncertainty. The lidar and ceilometer provide higher precision than radar for cloud-base detection by sensing small cloud droplets rather than precipitation-sized particles. Cloud-base and -top temperatures (T_{base} and T_{top}) were estimated by linearly interpolating ARM ship-based rawinsonde profiles during MARCUS (4–5 launches per day) to 5 min resolution using the corresponding H_{base} and H_{top} [21,47]. Liquid water path (LWP) was retrieved using a physical-iterative algorithm applied to MWR brightness temperatures at 23.8 and 31.4 GHz, with uncertainties of 15–30 g m⁻² [48,49]. To avoid wet-radome effects, only cases with MWR-derived LWP between 20 and 700 g m⁻² were retained for analysis [21].

A key limitation in decomposing cloud and drizzle reflectivity profiles from CloudSat CPR observations is the lack of dedicated CPR cloud-base and cloud-top height products. Although collocated CALIPSO lidar measurements can provide cloud boundary information, they were not used in this study because lidar attenuation and sampling mismatches with CPR can introduce additional uncertainties when directly combined with radar-detected profiles. Instead, cloud boundary estimation for CloudSat CPR profiles follows the methodology developed in [23], as summarized in Appendix C. This approach provides a reasonable approximation in cases where ceilometer- or radiosonde-derived cloud boundary products are unavailable. Cloud and drizzle reflectivity profiles (Figure A2 in Appendix C) are subsequently segregated following the method in [21,45]. It should be noted that CloudSat CPR signals are strongly affected by near-surface attenuation and surface clutter [33], with no reliable cloud detection below ~ 500 m. Furthermore, the cloud boundaries estimated from CloudSat CPR are coarser owing to its vertical resolution of ~ 240 m.

The empirical r_e – Z and LWC – Z relationships derived from aircraft in situ measurements presented in [29] were applied to M-WACR and CPR reflectivity to retrieve vertical profiles of cloud and drizzle effective radius ($r_{e,c}$, $r_{e,d}$) and liquid water content (LWC_c , LWC_d). Cloud liquid water path (LWP_c , g/m²) for M-WACR cloud profiles was estimated following [45], as

$$LWP_c = LWP_{MWR} - \int LWC_d dz, \quad (1)$$

where dz is the M-WACR range gate height (30 m), and LWP_{MWR} is the microwave radiometer-retrieved LWP during MARCUS. For CloudSat CPR, LWP_c is directly computed as $LWP_c = \int LWC_c dz$, with $dz = 240$ m corresponding to the CPR vertical resolution. The retrieved cloud LWP_c and drizzle LWP_d ($= \int LWC_d dz$) are then used to derive layer-mean LWC for cloud and drizzle, respectively, as $\overline{LWC} = LWP/\Delta H$. Here, ΔH denotes the cloud-layer thickness from cloud base to cloud top for cloud retrievals, as well as the drizzle-layer thickness from drizzle base (or layer base) to drizzle top for drizzle retrievals.

The cloud-droplet number concentration (N_c , cm⁻³) was estimated following [29,45], as

$$N_c = \frac{3 \overline{LWC_c}}{4\pi\rho_w \overline{r_{e,c}}^3} \exp(3\sigma_x^2), \quad (2)$$

where ρ_w is the density of liquid water, σ_s is set to the constant value of 0.4 as determined from aircraft CDP droplet spectra, and $\overline{r_{e,c}}$ represents the liquid-water-content-weighted mean cloud-droplet effective radius over the cloud layer. N_c is assumed to remain constant throughout the vertical extent of the cloud, following [45]. This assumption leads to a linear increase in LWC_c with height and a corresponding linear growth of the square root of cloud reflectivity ($\sqrt{Z_c}$), which is used to extract cloud reflectivity profiles.

The influence of drizzle on retrieved N_c and optical depth was found to be relatively minor in [6], likely due to only small perturbations in both LWP_c and $r_{e,c}$ [50]. The drizzle median radius ($r_{m,d}$, μm) was calculated from $r_{e,d}$, following [50]:

$$r_{m,d} = \frac{\Gamma(3+\mu)(3.67+\mu)}{\Gamma(4+\mu)} r_{e,d}, \quad (3)$$

where μ is the gamma shape parameter for drizzle, set to 0.5 based on aircraft 2D-S spectra. The drizzle median radius is then used to estimate drizzle number concentration (N_d) using a moment-based gamma distribution formulation that combines the drizzle parameterization of [45] with the LWC_d relationship from [29]:

$$N_d = \frac{10^6}{C_\mu \rho_w} \frac{\overline{LWC_d}}{r_{m,d}^3}, \quad (4)$$

where $C_\mu = \frac{4\pi}{3} \frac{\Gamma(4+\mu)}{\Gamma(1+\mu)(3.67+\mu)^3}$. Here, N_d is in cm^{-3} and is assumed to increase linearly from below cloud base to cloud top [51,52]. The layer-mean LWC was used to retrieve N_c and N_d instead of the vertically resolved LWC for cloud and drizzle in Equations (2) and (4), respectively. Since LWC profiles were derived from empirical relationships of the form $B \cdot \exp(0.115Z)$ with fixed coefficients, this approach preserves the variability of N_d within the cloud layer while maintaining N_c as vertically uniform.

Figures 2 and 3 illustrate a selected case of retrieved cloud and drizzle reflectivities from M-WACR and CPR, along with their corresponding retrieved microphysical properties. Figure 2a,e show the decomposed cloud and drizzle reflectivity profiles derived from M-WACR reflectivity measurements following the method of [45] as discussed in Appendix C. The retrieved cloud-droplet r_e and LWC profiles generally increase with height and then decrease toward cloud top due to entrainment, whereas the drizzle microphysical properties show opposite vertical trends with discontinuous structures. The cloud and drizzle microphysical properties retrieved from CloudSat CPR in Figure 3 were also obtained following [45] and show similar vertical structures to those in Figure 2.

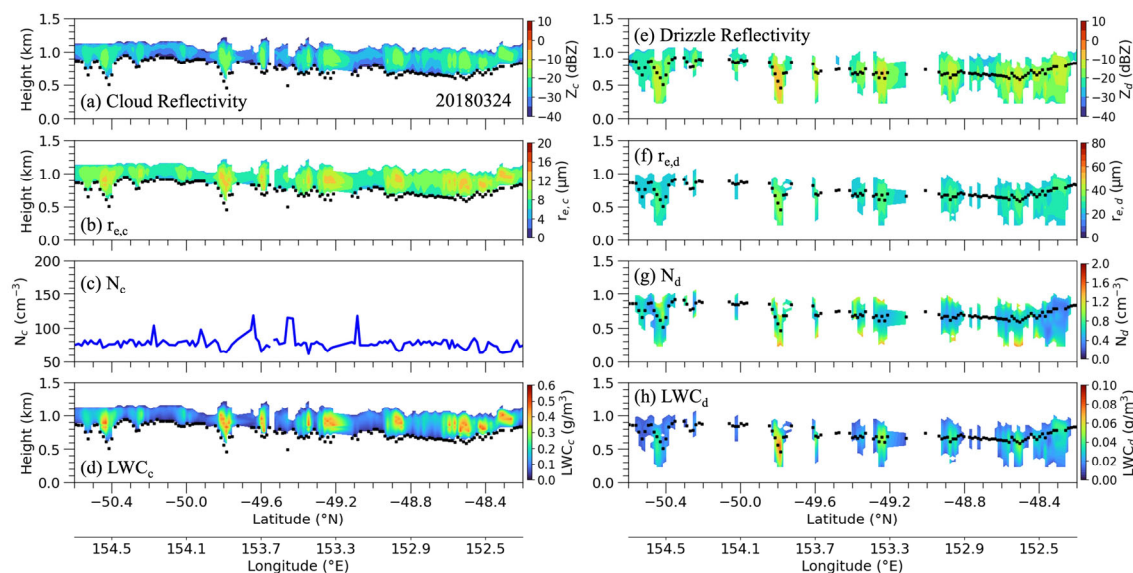


Figure 2. Cloud and drizzle radar reflectivity and microphysical properties retrieved from MARCUS M-WACR ship-based measurements on 24 March 2018. The selected time period corresponds to liquid-dominant low-level clouds and precipitation. The left column represents cloud measurements, (a) Z_c (dBZ), (b) $r_{e,c}$ (μm), (c) N_c (cm^{-3}), (d) LWC_c (gm^{-3}). The right columns (e,h) are the same but for drizzle measurements. The black dots represent the Ceilometer/MPL best-estimate cloud base heights.

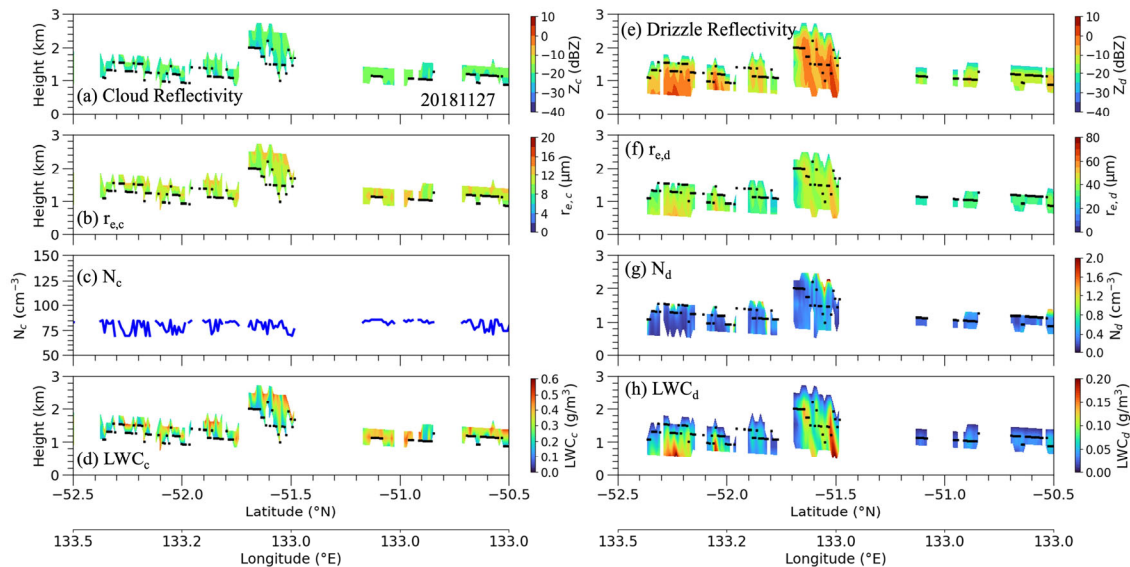


Figure 3. Same as Figure 2 but for cloud and drizzle radar reflectivity and microphysical properties retrieved from CloudSat CPR reflectivity measurements from a swath on 27 November 2018. The black dots represent the approximated cloud-base heights from CPR profiles.

3. Results

This section presents the statistical comparison of cloud and drizzle properties observed from the three platforms (SOCRATES, MARCUS, and CloudSat) for single-layer, liquid-dominant MBL cloud cases. Section 3.1 examines the macrophysical cloud properties and boundary characteristics, while Section 3.2 compares cloud and drizzle microphysical properties and vertical structures derived from SOCRATES airborne in situ observations with retrievals from the MARCUS ship-based and CloudSat satellite platforms. A total of 1136 five-minute samples (16.5% of all MARCUS cloud cases) were selected following [21] and further constrained to fall within the latitude–longitude grid box shown in Figure 1 to match the SOCRATES sampling domain. The SOCRATES dataset includes 87 profiles (~7329 CDP samples) and 50 profiles (~3564 2D-S samples) at 1 Hz resolution. CloudSat data were extracted for all valid swaths within the study region during the selected time period. A total of 164,808 CloudSat CPR profiles satisfying the cloud-selection criteria were retained for analysis. Each CPR profile represents a nadir-viewing radar observation with an approximate horizontal footprint of $1.7 \text{ km} \times 1.4 \text{ km}$, pulse length of 480 m, vertical range-bin spacing of 240 m, and lowest reliable cloud detection height of ~500 m. The large sample size reflects the continuous satellite sampling over the selected SO domain during November–March 2015–2020. Section 3.3 examines the sensitivity of the retrieved cloud and drizzle microphysical properties to biases in reflectivity and DSD measurements. Extreme outlier values were excluded to prevent undue influence on the reported mean estimates in the following sections.

3.1. Cloud Macrophysical Properties from Derived Three Platforms

In situ cloud boundaries observed during SOCRATES were identified from valid cloud profiles sampled by the CDP (total 87 cases; Figure A1 in Appendix B), where cloud-droplet number concentrations satisfied $N_c > 5 \text{ cm}^{-3}$ and $LWC_c > 0.01 \text{ gm}^{-3}$ [28,52]. Aircraft-measured T_{base} and T_{top} were derived from in situ ambient temperature measurements by mapping them to the corresponding H_{base} and H_{top} , respectively. Furthermore, the column-integrated LWP for cloud profiles sampled by the in situ probes during SOCRATES was calculated by vertically integrating the LWC throughout the entire cloud layer [23].

Figure 4 illustrates the probability density functions (PDFs) of H_{base} and H_{top} , their corresponding T_{base} and T_{top} , and cloud layer thickness ($H_{thickness} = H_{top} - H_{base}$). Cloud LWP was derived from in situ profiles for aircraft, microwave radiometer retrievals during MARCUS, and approximate estimates from CloudSat CPR observations, as discussed in Section 2. In the absence of collocated temperature profiles matched to the CloudSat swaths and vertical resolution, T_{base} and T_{top} could not be directly determined from the CloudSat observations. Nevertheless, these temperatures are expected to be comparable to those derived from MARCUS and SOCRATES measurements, given the close spatial and temporal overlap among the three observing platforms during the study period.

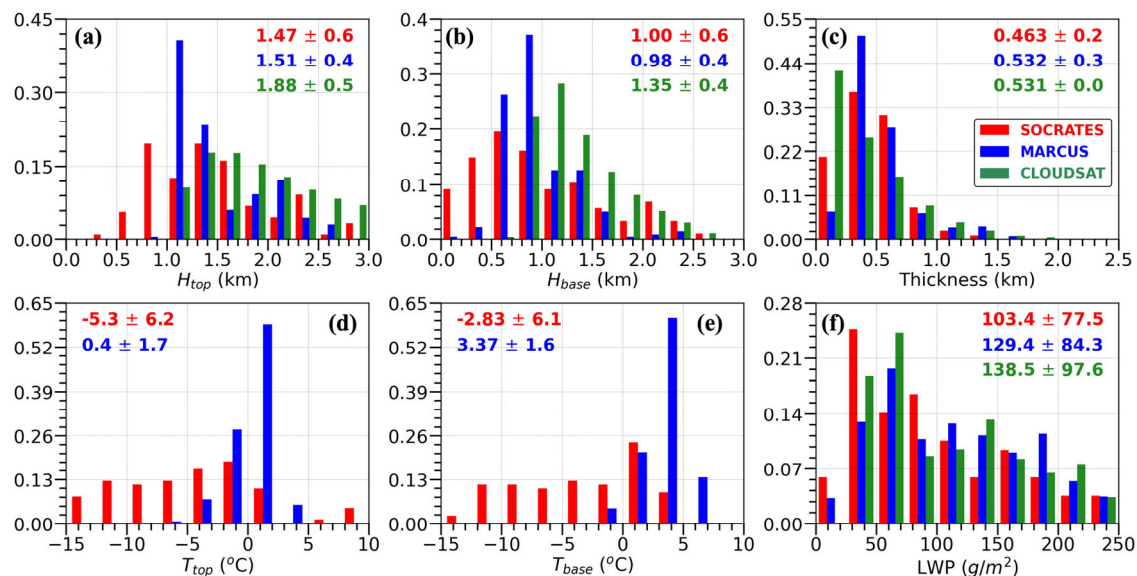


Figure 4. Frequency histograms of cloud macrophysical properties—(a) H_{top} (km), (b) H_{base} (km), (c) Cloud thickness (H_{thick} , km), (d) T_{top} (°C), (e) T_{base} (°C), and (f) LWP (g/m²)—derived from the three platforms: SOCRATES airborne in situ measurements, MARCUS ship-based (surface) observations, and CloudSat (CPR) satellite retrievals. The values reported in the legend indicate the mean and standard deviation for each dataset.

As shown in Figure 4a–c, most H_{top} and H_{base} values across the three observing platforms are below 1.5 km, with modal values between 0.5 and 1.5 km. The mean H_{top} and H_{base} values during SOCRATES and MARCUS show close agreement, differing by only 0.04 km and 0.02 km, respectively. The H_{top} and H_{base} heights estimated from CloudSat CPR profiles show noticeable differences from their airborne and ship-based counterparts, primarily because of CloudSat’s coarser vertical resolution (~240 m compared with ~30 m for MARCUS) and its nadir-viewing geometry. The mean H_{top} and H_{base} derived from CloudSat are approximately 0.4 km higher than their corresponding SOCRATES and MARCUS estimates.

As discussed previously, the CPR cannot reliably detect low clouds below ~500 m because of signal attenuation and contamination from surface clutter [33]. These limitations introduce a systematic low-cloud detection bias in CPR retrievals relative to the airborne and ship-based observations, primarily affecting cloud-base detection. As a result, CloudSat preferentially samples cloud layers with bases above the clutter-affected region, contributing to the observed differences in H_{base} and H_{top} relative to the aircraft and ship-based datasets. Despite differences in the mean H_{top} and H_{base} values among the datasets, the CloudSat distributions exhibit broad consistencies with MARCUS and SOCRATES in terms of their occurrence frequencies at heights above 1 km. This consistency likely reflects the relatively homogeneous nature of the selected low-level cloud population (<3 km) across the study domain.

The cloud-layer thickness is generally consistent across platforms, with mean values of 0.46 km (SOCRATES) and 0.53 km (MARCUS and CloudSat). This suggests that despite CloudSat's coarser vertical resolution, its relatively higher estimates of H_{top} and H_{base} still yield comparable cloud-layer thicknesses to those from the airborne and ship-based observations. A larger spread in H_{base} and H_{top} is observed during SOCRATES, characterized by frequent occurrences of both lower bases and higher cloud tops. However, the lower mean layer thickness suggests that most SOCRATES sampled clouds were relatively shallow despite the broader variability in H_{base} and H_{top} heights, with a limited number of cases extending to depths approaching ~3 km.

The histograms of T_{top} and T_{base} exhibit notable differences between SOCRATES and MARCUS profiles (Figure 4d,e). The mean T_{top} and T_{base} values from SOCRATES are -5.3°C and -2.8°C , respectively, whereas those from MARCUS are 0.4°C and 3.4°C . Although both datasets were collected within the same spatiotemporal region, the observed temperature differences primarily reflect differences in measurement approach and sampling characteristics, particularly between interpolated profile-based estimates and direct in situ aircraft observations. During MARCUS, temperatures derived from linearly interpolated rawinsonde or ERA5 profiles at the estimated H_{base} and H_{top} [21] tend to be higher, as they represent smoothed, large-scale environmental conditions rather than localized in-cloud thermodynamic variability. In contrast, in situ sensors onboard the SOCRATES GV aircraft directly sampled air temperatures within cloud layers, thereby capturing finer-scale thermodynamic structure and localized variability. As a result, the differences in T_{top} and T_{base} between SOCRATES and MARCUS in Figure 4d,e primarily reflect their measurement differences, rather than any systematic differences in the ambient thermodynamic conditions. Additionally, although many of the observed T_{top} and T_{base} values are below 0°C , the selected cloud population remains predominantly liquid-dominant, consistent with previous observations demonstrating the frequent occurrence of SLW in SO MBL clouds (e.g., [5,23]).

The PDFs of cloud LWP (Figure 4f) across the three platforms show overall consistency, with mean values of 103.4, 129.4 and 138.5 gm^{-2} , respectively for SOCRATES, MARCUS and CloudSat. Their differences are generally comparable to the reported LWP uncertainty ($\sim 20\text{ gm}^{-2}$) retrieved from ship-based microwave radiometer measurements. MARCUS and CloudSat exhibit similar cloud-layer thicknesses; however, the coarser vertical resolution of CloudSat contributes to slightly higher LWP estimates. The layer-mean cloud LWC values ($\overline{LWC}_c = LWP/\Delta H$) are 0.22 gm^{-3} , 0.24 gm^{-3} , and 0.26 gm^{-3} for SOCRATES, MARCUS, and CloudSat, respectively, indicating broadly comparable cloud water concentrations across the three platforms. Overall, MBL clouds over the SO sampled by the three platforms remain consistently liquid-dominant.

3.2. Cloud and Drizzle Microphysical Properties Derived from Three Platforms

3.2.1. Statistical Comparisons

The frequency histograms comparing MBL cloud and drizzle microphysical properties retrieved from SOCRATES, MARCUS M-WACR, and CloudSat CPR observations are shown in Figure 5. The SOCRATES cloud and drizzle properties were derived from CDP and 2D-S probe measurements, respectively, whereas those for MARCUS and CloudSat were obtained using retrievals based on decomposed cloud and drizzle reflectivity profiles. The cloud reflectivity values (Figure 5a) for SOCRATES and MARCUS show good agreement, with mean values -26.5 and -27.1 dBZ, respectively. The CloudSat CPR experienced instrument sensitivity degradation over time, decreasing from approximately -30 to -26 dBZ [18,33]. Consequently, the mean Z_c reported by CloudSat is ~ 6 dBZ higher than that observed by both SOCRATES and MARCUS M-WACR, reflecting this reduced sensitivity and associated retrieval bias.

The N_c values retrieved from SOCRATES CDP measurements are broadly distributed between 0 – 150 cm^{-3} , while N_c from MARCUS and CloudSat show near-normal distributions, with most values concentrated around 50 – 100 cm^{-3} (Figure 5b). The broader SOCRATES N_c distribution reflects the direct, high-resolution in situ sampling of cloud droplet size distributions by the CDP probe at 1 Hz, which captures the natural variability present within the sampled cloud layers. In contrast, MARCUS and CloudSat N_c values represent retrieved layer-mean quantities, which smooth part of this variability and result in comparatively narrower distributions. The $r_{e,c}$ values for SOCRATES and MARCUS also follow near normal distributions (Figure 5c), with mean values 9.3 and 8.4 μm , respectively, whereas CloudSat shows slightly larger $r_{e,c}$ values with a mean of ~ 10.4 μm , consistent with its higher cloud reflectivity. Similarly, LWC_c for SOCRATES and MARCUS demonstrate good agreement, with mean values 0.21 and 0.16 gm^{-3} , respectively, while LWC_c for CloudSat yields a higher mean of ~ 0.27 gm^{-3} (Figure 5d). The mean LWC_c values in Figure 5d are positively correlated with their corresponding Z_c , N_c , and $r_{e,c}$ results, showing consistency between cloud reflectivity values and their retrievals.

The frequency histograms comparing drizzle microphysical properties across the three platforms are shown in Figure 5e–h. Drizzle reflectivities (Z_d) derived from all three platforms exhibit near-normal distributions. The higher mean Z_d value (~ -10.5 dBZ) from CloudSat CPR is again consistent with its higher detection threshold (~ -26 dBZ), which tend to preferentially sample stronger reflectivity signals. In contrast, SOCRATES and MARCUS M-WACR report lower mean Z_d values (-13.3 and -16.9 dBZ, respectively), owing to higher instrument sensitivity and improved capability to detect weaker drizzle signals, particularly near the cloud base and surface.

Drizzle-drop N_d distributions for MARCUS and SOCRATES are comparable, with mean values of 0.70 cm^{-3} and 0.83 cm^{-3} , respectively, although SOCRATES 2D-S exhibits a larger spread due to greater variability in the sampled drizzle population. In contrast, CloudSat shows a substantially lower mean N_d (~ 0.43 cm^{-3}), consistent with its larger retrieved $r_{m,d}$, which reduces N_d for a given layer-mean $\overline{LWC_d}$. The lower mean N_d retrieved from CloudSat is consistent with the slight shift of the distribution toward smaller N_d values and the reduced frequency of larger N_d occurrences compared to SOCRATES and MARCUS. Nevertheless, the overall N_d distributions remain broadly similar, indicating that the three platforms sample a comparable range of drizzle number concentrations. The observed differences likely reflect the effects of the CloudSat sampling geometry and retrieval methodology, which represent cloud and drizzle properties at substantially coarser spatial scales than the aircraft and ship-based observations. The $r_{e,d}$ and LWC_d distributions exhibit broadly comparable distributions across the three platforms, with mean values of 33.5 μm and 0.05 gm^{-3} for SOCRATES, 29.1 μm and 0.02 gm^{-3} for MARCUS, and 38.3 μm and 0.05 gm^{-3} for CloudSat. The relatively higher $r_{e,d}$ and LWC_d values from CloudSat CPR

are indicative of its sampling bias towards stronger drizzle reflectivities, resulting from coarser resolution and reduced sensitivity to weaker reflectivity returns.

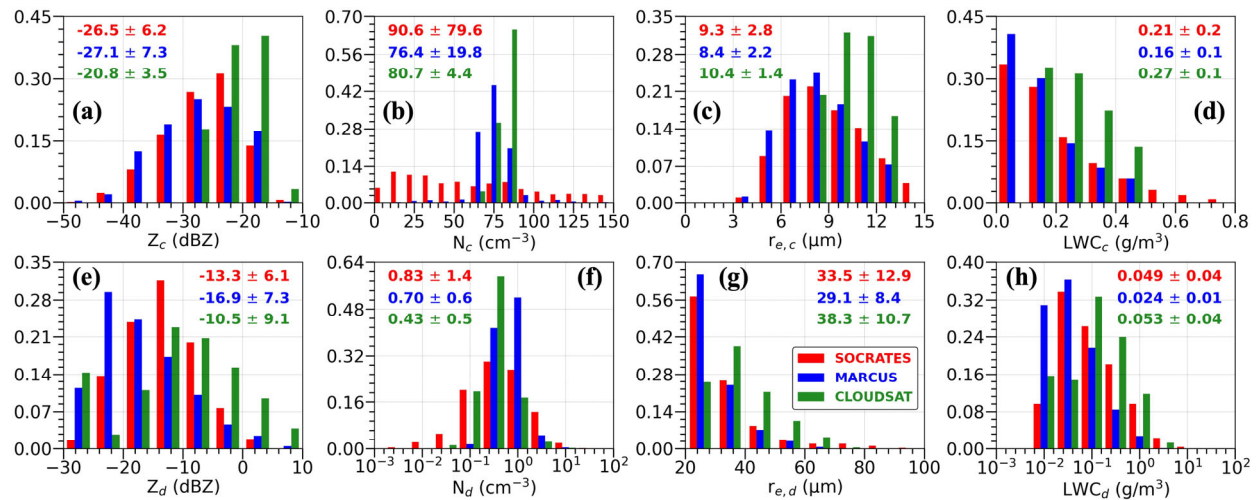


Figure 5. Frequency histograms of cloud (a–d) and drizzle (e–h) microphysical properties derived from three platforms: SOCRATES 2D-S airborne measurements (red), MARCUS M-WACR ship-based observations (blue), and CloudSat CPR satellite observations (green). Values in the legend represent the mean and standard deviation for each dataset.

Considering the aircraft in situ measurements as the reference, the percent differences between the central statistics of the retrieved microphysical properties were calculated following the method of [21] as $\% \text{ diff} = 100\% \times \frac{|\text{mean1} - \text{mean2}|}{(\text{mean1} + \text{mean2})/2}$, i.e., the ratio of the absolute difference to the average of the two compared values. For cloud properties, the MARCUS M-WACR retrievals show mean differences of 17% (N_c), 10.2% ($r_{e,c}$), and 25% (LWC_c) relative to SOCRATES CDP measurements. Corresponding CloudSat CPR retrieved N_c , $r_{e,c}$, LWC_c retrievals differ by 11.6%, 11.2%, and 25%, respectively. For drizzle microphysical properties, the M-WACR retrievals of N_d , $r_{e,d}$, LWC_d show mean differences of 17%, 14.1%, and 68.5% respectively, whereas the CPR retrievals show mean differences of 63.5%, 13.4%, and 7.8% relative to the SOCRATES 2D-S measurements. Overall, these comparisons indicate that both radar-based retrievals are broadly consistent with in situ observations within expected retrieval and sampling uncertainties. Larger deviations are observed in N_d for CPR and in LWC_d for M-WACR, likely reflecting variability in drizzle sampling and associated retrieval assumptions. In contrast, differences in cloud properties remain comparatively smaller and more consistent across the three observing systems.

The retrieved cloud and drizzle microphysical properties from MARCUS M-WACR measurements in this study were further evaluated through comparison with corresponding M-WACR retrievals reported by [21], based on the method of [45], over the same latitude–longitude domain considered in this study. The mean percentage differences between the two approaches were approximately 10.5% (2.9%) for N_c (N_d), 9.1% (5%) for $r_{e,c}$ ($r_{e,d}$), and 17.1% (22.2%) for LWC_c (LWC_d). These differences generally fall within the median retrieval uncertainties reported in [45], which are approximately 35% (50%), 15% (30%), and 30% (50%) for N_c (N_d), $r_{e,c}$ ($r_{e,d}$), and LWC_c (LWC_d), respectively.

A similar comparison was also performed for the CloudSat CPR-derived cloud and drizzle properties against forward-model-based retrievals from the CloudSat Radar-Only Cloud Water Content (CWC-RO) product [53] for a subset of all available CPR data over the period of Nov–Dec 2017. Because the CWC-RO product does not explicitly separate cloud and drizzle, a threshold liquid effective radius of 20 μm was applied to partition the

retrievals into cloud ($r_e < 20 \mu\text{m}$) and drizzle ($r_e > 20 \mu\text{m}$) regimes. This threshold-based partitioning is expected to introduce some differences in the frequency distributions. The mean percentage differences between the two approaches were approximately 27.8% (47.8%) for N_c (N_d), 25.7% (42.3%) for $r_{e,c}$ ($r_{e,d}$), and 3.6% (57.1%) for LWC_c (LWC_d).

These comparisons are intended as contextual consistency checks across independent retrieval frameworks rather than as absolute validation. Differences in retrieval assumptions, measurement sensitivity, sampling volume, and cloud–drizzle partitioning inherently lead to variability in the derived distributions. The corresponding frequency distributions corresponding to these intercomparisons are provided in Figures S1 and S2 of the Supplementary Material. Overall, the general consistency between the retrieval approaches suggests a comparable representation of cloud and drizzle microphysical characteristics across the three datasets. However, these results should only be interpreted as a contextual consistency assessment rather than absolute validation.

Given the higher threshold sensitivity of CloudSat CPR reflectivity measurements ($> -26 \text{ dBZ}$), a statistical comparison was also performed by subsetting the observed reflectivities from the three platforms into three interval bins to examine how differences in reflectivity sensitivity influence the retrieved r_e and LWC . Since N_c and N_d are secondary quantities derived from layer-mean LWC and characteristic radius, they are not included in the reflectivity-subset analysis to avoid ambiguity in interpreting reflectivity-dependent variability but are instead presented in Supplementary Table S1.

Table 1 presents the estimated means and % differences for the cloud and drizzle microphysical properties from the three platforms for each reflectivity bin. In the reflectivity range between -50 and -26 dBZ , which lies below the CPR detection sensitivity, the mean % differences in $r_{e,c}$ and LWC_c for SOCRATES in situ measurements and the corresponding MARCUS M-WACR retrievals are approximately 9.9% and 24.9%, respectively. Similarly, in the -26 to -10 dBZ range where all three platforms report valid observations, the mean % differences in $r_{e,c}$ and LWC_c between airborne in situ CDP measurements and M-WACR are 6.5%, and 17.5%, respectively, while they are 6.1% and 13.8%, respectively, between CDP and CPR retrievals.

Additionally, in the drizzle reflectivity range of -30 and -10 dBZ , the mean % differences between airborne in situ 2D-S measurements and M-WACR, CPR retrievals are $\sim 14.5\%$ and 2.7% for $r_{e,d}$ and 55.3% and 35.3% for LWC_d . Similarly, within the -10 and 10 dBZ range, the corresponding mean differences are $\sim 0.9\%$ and 5.7% for $r_{e,d}$ and 28.6% and 8.7% for LWC_d . Notably, the mean values presented in Table 1 indicate a generally good agreement between the zenith-pointed M-WACR observations and nadir-pointing CPR retrievals. The corresponding PDF histogram comparing cloud and drizzle microphysical properties across the three platforms for each reflectivity subset bin are illustrated in Figures S3 and S4 of the Supplementary Material.

Table 1. Means and standard deviations of cloud and drizzle microphysical properties derived from the three platforms for separate reflectivity range bins.

	Reflectivity Range (dBZ)	Effective Radius (μm)			Liquid Water Content (gm^{-3})		
		Socrates (CDP & 2D-S)	MARCUS M-WACR	CloudSat CPR	Socrates (CDP & 2D-S)	MARCUS M-WACR	CloudSat CPR
Cloud	-50 to -26	7.4 ± 1.7	6.7 ± 1.1	-	0.09 ± 0.06	0.07 ± 0.03	-
	-26 to -10	11.1 ± 2.4	10.37 ± 1.3	10.44 ± 1.4	0.31 ± 0.2	0.26 ± 0.1	0.27 ± 0.1
Drizzle	-30 to -10	29.7 ± 6.8	25.5 ± 3.8	28.9 ± 3.2	0.03 ± 0.02	0.017 ± 0.01	0.021 ± 0.01
	-10 to 10	42.6 ± 18.3	42.2 ± 7.4	45.1 ± 8.9	0.12 ± 0.1	0.09 ± 0.03	0.11 ± 0.05

To assess the potential influence of temporal sampling differences among the SOCRATES (January–February 2018), MARCUS (November 2017–March 2018), and CloudSat (November–March 2015–2020) datasets, annual mean CloudSat-derived cloud macrophysical and microphysical properties were calculated for each NDJFM season from 2015 to 2020 (presented in Supplementary Table S2a,b). The annual mean retrieved macrophysical (H_{top} , H_{base} , $H_{thickness}$, and LWP) and microphysical (Z , r_e , and LWC) properties exhibited only minor year-to-year variations and remained close to their corresponding five-year mean values.

3.2.2. Vertical Distributions

The vertical distributions of the cloud and drizzle microphysical properties derived from the three platforms are illustrated in Figure 6. The heights were normalized using $H_i = \frac{H-H_{base}}{H_{top}-H_{base}}$, for $H > H_{base}$, and $H_i = \frac{H-H_{base}}{H_{base}-D_{base}}$, for $H < H_{base}$, where D_{base} represents the drizzle base (or drizzle layer base), defined as the lowest height with a valid radar reflectivity signal in drizzle cloud profiles. As shown in Figure 6, there are approximately five sub-layers between H_{base} and H_{top} where all three platforms provide simultaneous valid observations of cloud microphysical properties. Based on the observed cloud thickness for each platform, each sublayer thickness is approximately 100 m.

The normalized profiles of Z_c , $r_{e,c}$, and LWC_c (Figure 6a,c,d) show a near-linear increase from H_{base} to the center of the cloud layer ($H_i \sim 0.6$), followed by a gradual decrease towards H_{top} . This structure is consistent with condensational growth within the cloud layer and cloud-top entrainment effects in near the cloud top where evaporation of small cloud droplets provides additional water vapor for enhancing drizzle initiation [7,12,29,45]. Because $r_{e,c}$ and LWC_c are retrieved from the observed Z_c , their vertical structures are influenced by the retrieval framework while inheriting the vertical variability of the observed Z_c profile. N_c (Figure 6b) is presented as a cloud-layer mean due to the retrieval assumptions. SOCRATES shows a larger spread in N_c values, indicating broader in situ sampling of the cloud DSD, whereas MARCUS and CloudSat exhibit more concentrated distributions. This difference reflects the contrast between direct in situ sampling, which captures local cloud heterogeneity including cloud-edge and precipitating conditions, and retrieval-derived N_c , which is constrained by the bulk $\overline{LWC}/r_e^3$ scaling and therefore exhibits reduced variability. Similar behavior is also partially reflected in the N_d vertical distributions shown in Figure 6f.

Although only layer-mean N_c values are presented in Figure 6b to ensure consistency among the SOCRATES, MARCUS, and CloudSat datasets, the vertical distribution of N_c derived from the SOCRATES CDP observations is shown in Figure S5 of the Supplementary Material. The profile exhibits relatively weak vertical variability, with median N_c values remaining approximately between 80 and 90 cm^{-3} throughout the cloud layer. This near-uniform vertical structure supports the use of a layer-mean N_c for inter-platform comparisons, while the observed spread at each height reflects natural cloud microphysical variability as well as sampling variability associated with the in situ probe observations. Furthermore, the relatively uniform vertical N_c structure observed by the CDP is consistent with the assumption of vertically homogeneous N_c adopted in the MARCUS and CloudSat retrieval methodologies, further supporting the use of layer-mean N_c for inter-platform comparisons.

The vertical distributions of $r_{e,c}$ and LWC_c across normalized layers basically follow their corresponding Z_c profiles and are broadly symmetric for MARCUS and SOCRATES, with some deviations in CPR-based profiles at lower levels. The presence of larger cloud droplets near the upper cloud levels suggests that these droplets act as embryonic drizzle

drops, initiating the collection of smaller cloud droplets through collision–coalescence processes and subsequently forming larger drizzle drops [12].

This pattern is also evident in the normalized Z_d , $r_{e,d}$, and LWC_d profiles (Figure 6e,g,h), which generally increase from cloud top toward cloud base across all three platforms. This vertical structure is consistent with the presence of embryonic drizzle drops aloft and enhanced collision–coalescence as drops grow while falling. The increase in LWC_d toward H_{base} ($H_i \sim 0$) is consistent with collision–coalescence growth, whereby falling drizzle droplets collect smaller cloud droplets and gain liquid water mass. As a result, liquid water is transferred from the cloud-droplet population to the drizzle population, leading to increasing LWC_d despite decreasing N_d . In contrast, mean N_d profile (Figure 6f) decreases from cloud top toward the cloud base, while $r_{e,d}$ increases, reflecting the progressive growth of drizzle droplets. Although this behavior is partially influenced by the retrieval formulation, in which N_d is vertically extrapolated, it is also physically consistent with drizzle self-collection processes. As drops fall, collision–coalescence processes increase $r_{e,d}$ while reducing N_d . The decrease in N_d , $r_{e,d}$, and LWC_d near the drizzle base indicates net evaporation, consistent with the relatively dry sub-cloud conditions over the SO that enhance drizzle evaporation. The slight enhancement in N_d near drizzle base in Figure 6f for MARCUS likely arises from the sensitivity of the N_d retrieval to variations in the retrieved $r_{m,d}$, which can produce localized increases in the derived N_d profile despite the overall decrease in N_d from the cloud top towards the surface. Consequently, this localized enhancement likely reflects the combined effects of retrieval uncertainty for MARCUS N_d ($\pm 0.6 \text{ cm}^{-3}$) and the sensitivity of the retrieval methodology to variations in the retrieved $r_{m,d}$, and it should be interpreted within the context of the retrieval framework.

The vertical profiles of $r_{e,c}$, $r_{e,d}$, LWC_c , and LWC_d broadly resemble the structures of their corresponding reflectivity profiles (Z_c and Z_d). In contrast to cloud properties, drizzle microphysical properties exhibit slightly skewed distributions, with mean values exceeding the corresponding medians across most layers. These deviations likely reflect both retrieval constraints and instrumental sampling differences, with CPR-based profiles showing departures from SOCRATES and M-WACR, consistent with the higher reflectivity sensitivity of the CPR. Despite these differences, the drizzle microphysical profiles exhibit substantial consistency among the three platforms, similar to their cloud counterparts. Additionally, the absence of valid CloudSat CPR observations below $\sim 500 \text{ m}$ makes cross-platform comparisons in the lower levels (below $\sim 0.5 H_i$) less straightforward.

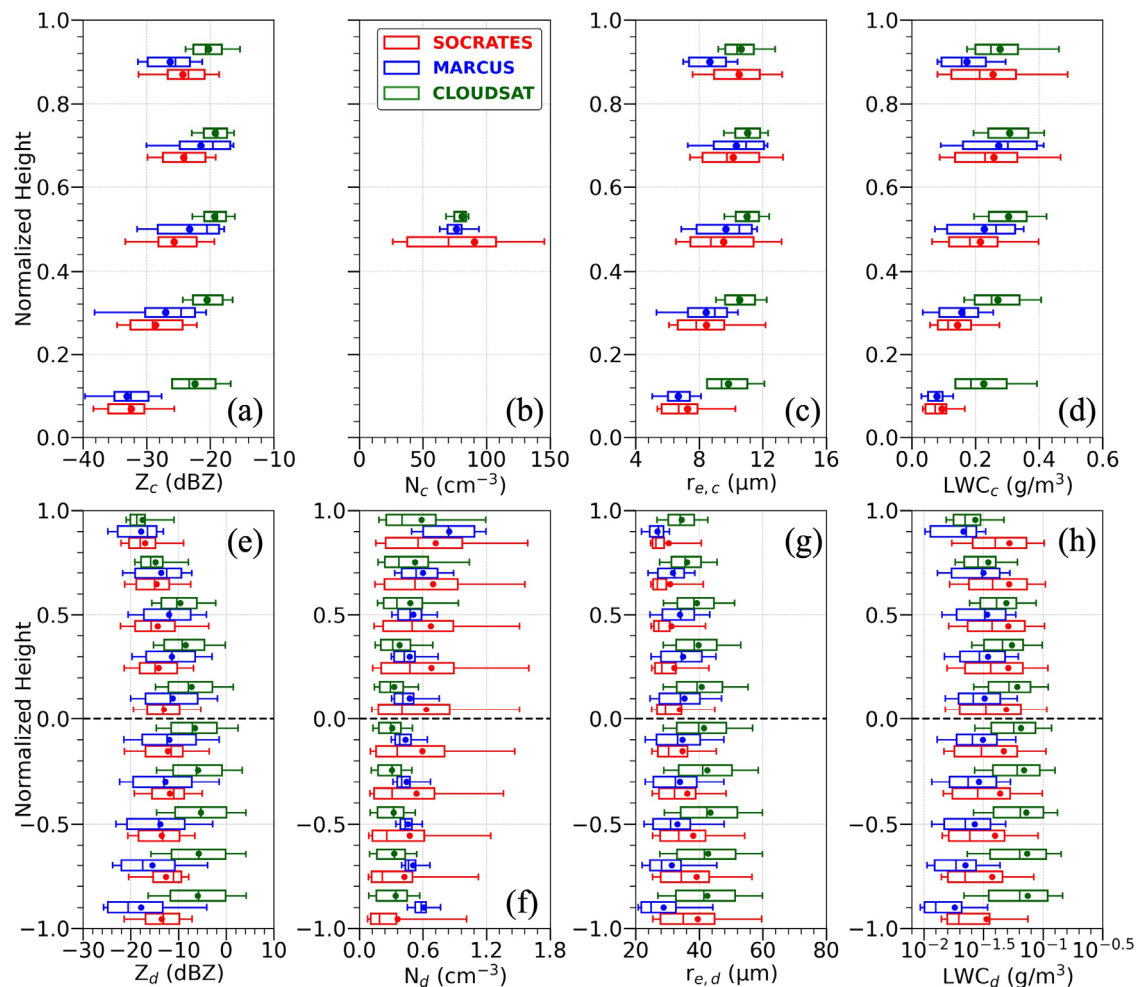


Figure 6. Vertical profiles of cloud (a–d) and drizzle (e–h) microphysical properties retrievals from SOCRATES CDP and 2D-S (red), MARCUS M-WACR (blue), and CloudSat CPR (green). The dots represent mean value, while the vertical lines from left to right represent 10%, 25%, 50%, 75% and 90% quartiles of the dataset. The profile mean values were estimated using a smoothing window average for each sub-layer. The y -axis represents normalized heights, where 1 is the cloud top (H_{top}), 0 is the cloud base (H_{base}), and -1 is the drizzle base (D_{base}).

3.2.3. Influence of Environmental Conditions on Cloud Properties

Meteorological conditions for MBL clouds over the SO were derived from hourly surface-level ERA5 reanalysis data. These data were spatially and temporally collocated with the MARCUS cloud cases and were previously analyzed in detail in [21]. Therefore, we do not repeat the full analysis here but instead summarize the key findings to briefly discuss the influence of environmental conditions on cloud properties. Owing to the spatiotemporal matching, the environmental conditions are expected to be broadly consistent across the three platforms.

The mean surface pressure (Ps) is approximately 1012 hPa, with a relatively broad distribution that reflects the variable synoptic conditions over the SO. The mean relative humidity (RH) is around 80.9%, while the mean 2 m air temperature and sea surface temperature (SST) are approximately 8.85 °C and 9.85 °C, together supporting moderate atmospheric moisture content. The mean precipitable water vapor (PWV) is ~6.99 mm, indicating comparatively limited moisture availability for large droplet growth relative to MBL clouds observed over the ARM Eastern North Atlantic (ENA) site.

Lower tropospheric stability (LTS) spans a broad range (5–23 K, Figure 5a in [21]), corresponding to unstable (<13.5 K), mid-stable (13.5–18 K), and stable (>18 K) boundary layers. Lower LTS values indicate stronger instability and more frequent drizzling within mesoscale convective cellular structures [54]. Together, the broad range of LTS and relatively low PWV help explain the high drizzle frequency over the SO (~71.8%), reflecting the combined influence of diverse atmospheric regimes and limited moisture availability. These results suggest that drizzle frequently forms under unstable conditions, but its subsequent growth remains constrained by the relatively low PWV environment.

3.3. Sensitivity of Retrieved Microphysical Properties to Bias in Underlying Measurements

The ARM M-WACR observations during MARCUS have been reported to exhibit reflectivity values approximately 4–5 dB lower than those measured by the well-calibrated CloudSat CPR [21,33,46]. In addition, reflectivity measurements from SOCRATES carry an uncertainty of approximately 1–2 dB [23,55,56]. Therefore, assessing the impact of potential reflectivity biases on the retrieved microphysical properties from M-WACR and CPR is important, as the retrieval technique primarily relies on empirical relationships with reflectivity. Since the SOCRATES-based microphysical parameters (r_e and LWC) are derived directly from in situ DSD measurements, a sensitivity analysis based on dB perturbations was not performed for this dataset. Furthermore, as noted above, the sensitivities of N_c and N_d reflect nonlinear propagation through the retrieval framework rather than a direct response to reflectivity offsets or distribution-shape variations. Therefore, the primary offset sensitivity analysis is focused on r_e and LWC in the main text, while the corresponding responses of N_c and N_d are presented in Table S3 of the Supplementary Material.

As listed in Table 2, using the +0.0 dB case as the reference, positive reflectivity perturbations (+2, +4, and +6 dB) produce systematic increases in the retrieved cloud and drizzle microphysical properties. Specifically, $r_{e,c}$ increases by approximately 7.7–22.9% for both MARCUS and CloudSat, while LWC_c increases by approximately 22.8–66.5%. Similarly, $r_{e,d}$ increases by 3.3–16.2% (MARCUS) and 7.4–15.1% (CloudSat), whereas LWC_d increases by 22.2–64.8% (MARCUS) and 23.3–66.7% (CloudSat). These changes are expected because the empirical retrieval relationships scale monotonically with radar reflectivity, yielding progressively larger retrieved particle sizes and liquid water contents with increasing reflectivity. Conversely, negative reflectivity perturbations (−2, −4, and −6 dB) produce nearly symmetric decreases in the retrieved microphysical properties, with no major differences in the overall sensitivity compared to the positive perturbations.

Overall, these results are physically consistent, as larger radar reflectivity values generally indicate the presence of larger hydrometeors and greater liquid water contents. Consequently, the empirical reflectivity–microphysics relationships yield systematically larger retrieved particle sizes and liquid water contents with increasing reflectivity bias. Furthermore, because the reflectivity perturbations are applied prior to the cloud–drizzle decomposition, the corresponding −15 dBZ interpolation height also shifts with the perturbed reflectivity profile, effectively shifting the cloud–drizzle partitioning by the same magnitude as the applied reflectivity perturbation (e.g., from −15 dBZ to −13, −11, and −9 dBZ for the +2, +4, and +6 dBZ sensitivity tests), with equivalent shifts toward lower reflectivity for the corresponding negative perturbations. Therefore, the reported sensitivity analysis evaluates not only the influence of reflectivity uncertainty on the retrieved microphysical properties but also the sensitivity of the effective cloud–drizzle partitioning within the retrieval framework.

The N_c values from both MARCUS and CloudSat show minimal sensitivity (<1%) to both positive and negative dB offsets, as the retrieval assumes a vertically uniform N_c throughout the cloud layer. In contrast, N_d shows greater sensitivity to reflectivity pertur-

bations. For negative dB offsets (−2 to −6 dB), N_d decreases by approximately 5.1–12.2% for MARCUS and 2.1–6.4% for CloudSat. For positive dB offsets (+2 to +6 dB), N_d increases by approximately 7.8–15.8% for MARCUS and 1.4–63% for CloudSat. This behavior is consistent with the retrieval dependence of N_d on the ratio of layer-mean $\overline{LWC_d}$ to $r_{m,d}^3$. Although both $r_{m,d}$ and LWC_d increase with higher positive dB offsets, the relative increase in layer-mean LWC_d is proportionally larger, leading to a net increase in N_d (Table S3).

Table 2. Sensitivities of reflectivity bias to the cloud and drizzle retrievals.

dBZ	$r_{e,c}$ (μm)		$r_{e,d}$ (μm)		LWC_c (gm^{-3})		LWC_d (gm^{-3})	
	MARCUS	CloudSat	MARCUS	CloudSat	MARCUS	CloudSat	MARCUS	CloudSat
	M-WACR	CPR	M-WACR	CPR	M-WACR	CPR	M-WACR	CPR
−6.0 dB	6.67	8.29	26.90	31.15	0.08	0.13	0.012	0.027
	(−22.9%)	(22.9%)	(−7.9%)	(−20.5%)	(−66.1%)	(−66%)	(−66.7%)	(−65%)
−4.0 dB	7.21	8.95	27.58	33.24	0.10	0.17	0.015	0.033
	(−15.3%)	(15.3%)	(−5.4%)	(−14%)	(45.6%)	(−45.2%)	(−46.2%)	(−46.51%)
−2.0 dB	7.78	9.67	28.28	35.62	0.13	0.21	0.019	0.042
	(−7.7%)	(7.7%)	(−2.9%)	(−7.1%)	(23.2%)	(−22.6%)	(−23.3%)	(−23.2%)
+0.0 dB	8.40	10.44	29.10	38.25	0.16	0.27	0.02	0.05
+2.0 dB	9.08	11.27	30.08	41.20	0.20	0.34	0.03	0.07
	(7.7%)	(7.7%)	(3.3%)	(7.4%)	(22.8%)	(23%)	(22.2%)	(23.3%)
+4.0 dB	9.80	12.17	31.69	41.21	0.25	0.42	0.04	0.08
	(15.3%)	(15.3%)	(8.5%)	(7.4%)	(44.9%)	(45.3%)	(42.6%)	(45.26%)
+6.0 dB	10.58	13.15	34.22	44.50	0.32	0.53	0.05	0.11
	(22.9%)	(22.9%)	(16.2%)	(15.1%)	(66.1%)	(66.5%)	(64.8%)	(66.7%)

The percent change from the +0.0 dB bias offset is shown in parenthesis.

The sensitivities of the empirical coefficients A and B on the underlying SOCRATES in situ CDP and 2D-S measured DSD parameters and number concentrations have been documented in [29]. Overall, the coefficient values exhibit only weak dependence on N_c and σ_x for cloud properties, and on N_d and μ for drizzle properties. Therefore, we further assess the sensitivity of the MARCUS M-WACR and CloudSat CPR cloud and drizzle microphysical retrievals to perturbations in σ_x and μ , respectively, using the SOCRATES-observed reference values of $\sigma_x = 0.4$ and $\mu = 0.5$. As listed in Table 3(a), for a ~10% change in σ_x , $r_{e,c}$ varies by ~3%, while LWC_c changes by ~30% on average for both MARCUS and CloudSat. Similarly, for a ~10% change in μ , $r_{e,d}$ changes by ~0.2% (MARCUS) and ~0.4% (CloudSat), while LWC_d changes by ~7.3% for MARCUS and ~5.4% for CloudSat, as listed in Table 3(b).

A decrease in σ_x narrows the cloud droplet spectrum, concentrating droplets near the mean size; this leads to a slight increase in $r_{e,c}$, while producing a more substantial amplification in LWC_c due to its cubic dependence on droplet radius. In contrast, perturbations in μ have a comparatively weaker effect on drizzle properties because the retrieval is primarily governed by larger radar reflectivity ($\propto D^6$), making $r_{e,d}$ and LWC_d only weakly sensitive to changes in the assumed spectral shape. Since N_c is retrieved as a fixed layer-mean quantity and N_d shows only limited sensitivity, variations in σ_x or μ primarily modify the assumed DSD shape rather than the bulk-integrated properties. As a result, both number concentrations remain largely unchanged (Supplementary Table S4). However, any minor adjustments in the inferred number concentrations likely reflect the scaling required to maintain internal consistency within the empirical relationships used in the retrieval framework.

Table 3. Sensitivities of microphysical retrievals to changes in (a) σ_x and (b) μ .

(a)		$r_{e,c}$ (μm)		LWC_c (gm^{-3})	
σ_x		MARCUS	CloudSat	MARCUS	CloudSat
		M-WACR	CPR	M-WACR	CPR
0.24		8.85 (5.1%)	10.99 (5.1%)	0.25 (45.3%)	0.42 (45.3%)
0.28		8.76 (4.1%)	10.88 (4.1%)	0.23 (36.1%)	0.39 (36.6%)
0.32		8.65 (2.9%)	10.75 (2.9%)	0.21 (25.8%)	0.35 (25.9%)
0.36		8.53 (1.5%)	10.60 (1.5%)	0.18 (13.5%)	0.31 (14%)
0.40		8.40	10.44	0.16	0.27
(b)		$r_{e,d}$ (μm)		LWC_d (gm^{-3})	
μ		MARCUS	CloudSat	MARCUS	CloudSat
		M-WACR	CPR	M-WACR	CPR
0.30		29.18 (0.28%)	38.53 (0.72%)	0.022 (−10.53%)	0.048 (−9.90%)
0.35		29.16 (0.20%)	38.45 (0.52%)	0.022 (−8.70%)	0.050 (−5.83%)
0.40		29.14 (0.14%)	38.38 (0.33%)	0.023 (−5.57%)	0.051 (−3.85%)
0.45		29.12 (0.08%)	38.31 (0.16%)	0.023 (−4.26%)	0.052 (−1.90%)
0.50		29.10	38.25	0.024	0.053

The percent change from the reference value ($\sigma_x = 0.4$ and $\mu = 0.5$) is shown in parenthesis.

4. Discussion

The multi-platform comparisons presented in Section 3 demonstrate that the cloud and drizzle macrophysical and microphysical properties derived using the SOCRATES-based empirical retrieval framework exhibit generally consistent statistical characteristics across airborne, ship-based, and satellite observations of Southern Ocean (SO) marine boundary layer (MBL) clouds. Although systematic differences exist because of variations in instrument sensitivity, spatial resolution, observing geometry, and sampling methodology, the overall agreement among the three observing systems supports the applicability of the empirical retrieval framework to statistically similar liquid-dominant cloud regimes observed by W-band radar.

The analysis should primarily be interpreted as an evaluation of cross-platform consistency rather than a fully independent validation because exact collocation among the three datasets cannot be achieved. Nevertheless, the relatively homogeneous SO MBL cloud regime sampled over the study region and season, together with the generally consistent cloud fractions reported by [33], provides a suitable basis for statistically comparing the three observing systems. Furthermore, the good agreement with independent MARCUS M-WACR retrievals [21,45] and the CloudSat CWC-RO product [53] provides additional confidence that the empirical retrieval relationships capture the dominant statistical characteristics of SO cloud and drizzle microphysics despite differences in retrieval methodology and sampling strategy.

Although the three platforms exhibit broadly consistent cloud and drizzle properties, systematic differences arise from their differing observational characteristics. The airborne in situ probes directly sample cloud particle size distributions at high spatial resolution, whereas the MARCUS M-WACR retrieves bulk cloud properties from vertically pointing

radar observations. In contrast, the CloudSat CPR samples substantially larger atmospheric volumes using a nadir-viewing geometry with coarser vertical resolution and reduced sensitivity to weak reflectivity signals. Its inability to reliably detect low clouds below approximately 500 m introduces a systematic low-cloud detection bias, contributing to relatively larger retrieved cloud boundaries, r_e , and LWC compared with the aircraft- and ship-based observations. Similarly, the broader distributions in number concentrations observed during SOCRATES primarily reflect direct sampling of natural cloud variability, whereas the MARCUS and CloudSat retrievals represent layer-mean quantities that smooth part of this variability.

The limited interannual variability observed in the five-year CloudSat dataset indicates that the selected multi-year observations provide a representative characterization of SO MBL clouds during the November–March period, supporting comparison with the shorter SOCRATES and MARCUS datasets despite their differing sampling periods. Furthermore, the improved agreement obtained when the analyses were restricted to common cloud–drizzle reflectivity intervals indicates that a substantial portion of the observed CloudSat differences can be attributed to its reduced sensitivity, coarser sampling geometry, and associated sampling characteristics rather than to systematic differences in the underlying cloud population.

The retrieved vertical structures are consistent with the conceptual evolution of warm MBL clouds undergoing drizzle formation. Z_c , $r_{e,c}$, and LWC_c generally increase from the cloud base toward the upper cloud layer before decreasing near the cloud top, consistent with condensational growth together with cloud-top entrainment that promotes the formation of embryonic drizzle droplets. In contrast, $r_{e,d}$ and LWC_d increase toward the cloud base while N_d decreases, reflecting collision–coalescence growth as falling drizzle droplets collect smaller cloud droplets. The subsequent reduction in drizzle properties below the cloud base is consistent with evaporation within the relatively dry sub-cloud environment near the surface. Although portions of these vertical structures reflect assumptions within the empirical retrieval framework, the overall profiles remain physically consistent with established conceptual models of drizzle growth and dissipation.

Several assumptions within the retrieval framework should be considered when interpreting the derived cloud and drizzle microphysical properties. Cloud N_c is retrieved as a vertically homogeneous layer-mean quantity, whereas drizzle N_d is derived from the retrieved $\overline{LWC_d}$ and $r_{m,d}$. The relatively weak vertical variability in N_c observed by the SOCRATES CDP measurements supports the assumption of vertically homogeneous N_c adopted in the MARCUS and CloudSat retrievals, although localized variability associated with entrainment, cloud edges, and precipitation are not explicitly represented within the retrieval framework.

Sensitivity analyses further demonstrate that uncertainties in radar reflectivity produce substantially larger variations in retrieved LWC than in r_e because of the exponential dependence of the empirical retrieval relationships on reflectivity. Because reflectivity perturbations are applied prior to cloud–drizzle decomposition, they also modify the effective cloud–drizzle partitioning within the retrieval framework. In contrast, perturbations in the assumed cloud and drizzle size-distribution parameters (σ_x and μ) produce comparatively smaller changes, indicating that retrieval uncertainty is primarily governed by reflectivity uncertainty rather than by the assumed distribution shape.

The observed cloud and drizzle characteristics are also consistent with the prevailing environmental conditions over the SO. The selected cloud population occurs under relatively cooler SST, moderate RH, comparatively low PWV, and a broad range of LTS. Together, these conditions favor frequent drizzle formation while limiting its subsequent growth through relatively limited atmospheric moisture availability and enhanced sub-cloud evaporation. Collectively, these results demonstrate that the empirical retrieval

framework provides a physically consistent and statistically robust characterization of SO MBL cloud and drizzle properties across airborne, ship-based, and satellite observations, supporting its application to similar liquid-dominant cloud regimes observed by W-band radar.

5. Conclusions

In this study, single-layer, liquid-dominant MBL clouds below 3 km were analyzed using observations from three platforms: the SOCRATES aircraft campaign, the MARCUS ship-based campaign, and the CloudSat satellite mission. The comparisons were constrained to spatiotemporally matched cloud cases for which the MARCUS and M-WACR platforms provided valid observations during November–March 2017–2018 within a common latitude–longitude domain over the SO, while CloudSat observations were drawn from a broader November–March 2015–2020 dataset over the same domain to provide a statistically robust satellite reference. The intercomparisons were conducted to evaluate the similarities and differences in the macrophysical and microphysical properties of MBL clouds as observed by the three platforms.

The major takeaways from the study are as follows:

1. Empirical relationships between reflectivity (Z), effective radius (r_e), and liquid water content (LWC), derived from SOCRATES in situ CDP and 2D-S DSD measurements [29], were applied to MARCUS M-WACR and CloudSat CPR reflectivity profiles to retrieve cloud and drizzle microphysical properties and number concentrations using an iterative retrieval framework.
2. H_{top} and H_{base} heights show good agreement across the three platforms, with most values below 1.5 km. Differences in CloudSat-derived heights arise from its coarser vertical resolution and reduced sensitivity to low clouds below ~500 m, limiting detection of shallow layers relative to aircraft- and ship-based observations. Temperature differences between SOCRATES and MARCUS reflect sampling and retrieval differences, with radiosonde-based MARCUS estimates yielding warmer values compared to locally sampled in situ measurements within supercooled layers during SOCRATES. Despite these differences, LWP and layer-mean LWC remain consistent across platforms within uncertainty, confirming liquid-dominant MBL cloud conditions.
3. Frequency histograms of cloud and drizzle microphysical properties show generally consistent distributions across the three platforms, with systematic differences linked to instrument sensitivity, sampling differences, and retrieval assumptions. Z_c from SOCRATES and MARCUS agree closely, while CloudSat exhibits higher values due to its sensitivity to higher reflectivities. Correspondingly, CloudSat retrievals yield mean N_c values (80.7 cm^{-3}) that lie between those observed during SOCRATES (90.6 cm^{-3}) and MARCUS (76.4 cm^{-3}), while exhibiting the higher mean $r_{e,c}$ ($10.4 \text{ }\mu\text{m}$) and LWC_c (0.27 g m^{-3}) compared to SOCRATES ($9.3 \text{ }\mu\text{m}$, 0.21 g m^{-3}) and MARCUS ($8.4 \text{ }\mu\text{m}$, 0.16 g m^{-3}). Drizzle properties show similar behavior, with mean Z_d of -13.3 dBZ (SOCRATES), -16.9 dBZ (MARCUS), and -10.5 dBZ (CloudSat); N_d of 0.83 cm^{-3} , 0.70 cm^{-3} and 0.43 cm^{-3} ; $r_{e,d}$ of $33.5 \text{ }\mu\text{m}$, $29.1 \text{ }\mu\text{m}$, and $38.3 \text{ }\mu\text{m}$; and LWC_d of 0.05 , 0.03 , and 0.05 gm^{-3} , respectively, consistent with CloudSat's bias toward stronger reflectivities and larger retrieved drizzle drops.
4. Across the common cloud reflectivity ranges (-26 to -10 dBZ), MARCUS M-WACR and CloudSat CPR retrievals agree well with SOCRATES in situ observations, with mean differences below 25% for N_c , $r_{e,c}$, and LWC_c . For drizzle reflectivity ranges (-30 to 10 dBZ), mean differences relative to SOCRATES 2D-S measurements range from ~ 1 to 55%, primarily due to sampling variability. In contrast, inter-radar comparisons between M-WACR and CPR show strong consistency, with mean differences of ~ 1 –

- 20% across all microphysical parameters, indicating robust and consistent cloud and drizzle representations. Differences in N_d remain larger due to its strong sensitivity to DSD variability and the cubic dependence on droplet size.
5. Normalized vertical profiles show that Z_c , $r_{e,c}$, and LWC_c generally increase from the cloud base to mid-levels and then decrease toward the cloud top, consistent with condensational growth and cloud-top entrainment processes. Drizzle properties display consistent vertical behavior across all platforms, with increasing $r_{e,d}$ and LWC_d but decreasing N_d toward the surface, reflecting collision–coalescence growth aloft, self-collection, and enhanced evaporation of drizzle in the drier sub-cloud layer.
 6. A sensitivity analysis of reflectivity biases (+2 to +6 dB) shows that retrieved r_e and LWC increase by ~3–23% and ~22–67%, respectively, while number concentrations vary from ~0.04% to 16% for MARCUS and ~0.04% to 63% for CloudSat. These responses are consistent with the stronger nonlinear dependence of microphysical retrievals on reflectivity and the physical growth processes that increase droplet size and liquid water content while reducing number concentration.
 7. Sensitivity tests using SOCRATES in situ measurements indicate that empirical coefficients and derived r_e and LWC values exhibit only weak dependence on DSD parameters N , σ_x , and μ , confirming the robustness of the retrieval framework across typical DSD variability. Additional perturbation experiments show that a 10% change in σ_x modifies $r_{e,c}$ by ~3% and LWC_c by ~30%, while similar perturbations in μ result in <8% changes in drizzle properties, indicating stronger sensitivity of cloud retrievals to σ_x than drizzle retrievals to μ .

The findings from this study provide key insights into the macrophysical and microphysical characteristics of liquid-dominant MBL clouds and drizzle over the SO, revealing both consistencies and differences across airborne, ship-based, and satellite platforms. Although they do not fully represent all SO synoptic conditions, these results offer a valuable reference for future modeling and observational studies of MBL cloud–precipitation processes. The cross-platform analysis provides crucial insights to help improve retrieval methodologies, reduce detection biases, and enhance the accuracy of vertical microphysical profiles. Furthermore, these findings inform the design of next-generation cloud radar systems and support the development of correction frameworks for historical CloudSat data, thereby helping to reduce systematic errors in cloud detection and profiling.

Supplementary Materials: The following supporting information can be downloaded at <https://www.mdpi.com/article/10.3390/rs18132262/s1>. Figure S1: Frequency histograms of the retrieved (a–c) cloud and (d–f) drizzle microphysical properties using the retrieval method in [45] (magenta) and the in situ-derived empirical relationships in [29] during SOCRATES (green); Figure S2: Comparison of cloud and drizzle microphysical properties between CloudSat CPR-derived retrievals (this study) and the CloudSat Radar-Only Cloud Water Content (CWC-RO) product; Figure S3: Frequency histograms of cloud microphysical properties from SOCRATES CDP measurements and MARCUS M-WACR, CloudSat CPR cloud-property retrievals for reflectivity range bins; Figure S4: Frequency histograms of drizzle microphysical properties from SOCRATES 2D-S measurements and MARCUS M-WACR, CloudSat CPR drizzle-property retrievals for reflectivity range bins; Figure S5: Vertical profile of N_c (cm^{-3}) from SOCRATES in situ CDP probe; Table S1: Mean and standard deviation of cloud and drizzle number concentration from the three platforms for reflectivity range bins; Table S2: Mean ($\pm$ std dev) values of the retrieved (a) macrophysical and (b) microphysical properties from CloudSat CPR measurements computed annually during the period November 2015–March 2020; Table S3: Sensitivities of retrieved number concentration and its underlying parameters to offsets in reflectivity bias; Table S4: Sensitivities of retrieved number concentration to changes in (a) σ_x and (b) μ .

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Data Availability Statement: All in situ datasets and relevant documentation from the NSF SOC-RATES campaign are available at the EOL data archive (<https://data.eol.ucar.edu/dataset/>) (accessed on 20 December 2025) and website (https://www.eol.ucar.edu/field_projects/socrates) (accessed on 20 December 2025). The in situ 2D-S probe dataset [43] is available at <https://doi.org/10.26023/8HMG-WQP3-XA0X>, and the CDP probe data [39] is available at <https://doi.org/10.5065/D6M32TM9>. The retrieval dataset during MARCUS along with the M-WACR measured cloud and drizzle reflectivities [21] can be found at <https://doi.org/10.25422/azu.data.23748969>, while the corresponding M-WACR measurements along with hydrometeor cloud masks (ARSLWACR1KOLLIAS, [36]) is available at <http://dx.doi.org/10.5439/1987455> (accessed on 20 December 2025) and the MWR retrieved LWP data [49] is at <http://dx.doi.org/10.5439/1027369> (accessed on 20 December 2025). The level 2 CloudSat CPR reflectivity data (2B-GEOPROF, [14]) and retrieved radar-only cloud water content product (2B-CWC-RO, [53]) datasets can be accessed at the CloudSat DPC site at <https://www.cloudsat.cira.colostate.edu/data-products/> (accessed on 20 January 2026).

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Abbreviations

The following abbreviations are used in this manuscript:

MBL	Marine Boundary Layer
SO	Southern Ocean
SOCRATES	Southern Ocean Clouds, Radiation, Aerosol Transport Experimental Study
MARCUS	Measurements of Aerosols, Radiation, and Clouds over the Southern Ocean
DSD	Droplet Size Distributions
M-WACR	Marine W-band ARM cloud radar
CPR	Cloud Profiling Radar
Z	Reflectivity
N	Number Concentration
r_e	Effective Radius
LWC	Liquid Water Content
$r_{m,d}$	Drizzle Median Radius
SLW	Supercooled Liquid Water
DOE	Department of Energy
ARM	Atmospheric Radiation Measurement
AMF	ARM Mobile Facility
MWR	Microwave Radiometer
MPL	Micropulse Lidar
CDP	Cloud Droplet Probe
2D-S	Two-Dimensional Stereo Particle Imaging Probe
HCR	HIAPER Cloud Radar

HSRL	High Spectra Resolution Lidar
GV	Gulfstream-V
LWP	Liquid Water Path
H _{top}	Cloud-top height
H _{base}	Cloud-base height
H _{thickness}	Cloud-layer thickness (H _{top} – H _{base})
T _{top}	Cloud-top temperature
T _{base}	Cloud-base temperature
CWC-RO	Radar-Only Cloud Water Content
Ps	Surface Pressure
SST	Sea Surface Temperature
PWV	Precipitable Water Vapor
LTS	Lower tropospheric stability
ENA	Eastern North Atlantic
PDF	Probability Density Function

Appendix A. Instruments and Measurements from Three Platforms over Selected Region

Table A1 lists all instruments and measurements used in this study, along with their associated sensitivities and uncertainties. The M-WACR provides ~30 m vertical resolution profiles of radar reflectivity, Doppler velocity, and spectrum width, with hydrometeor detection ranging from ~−50 to +20 dBZ up to 10 km and a nominal uncertainty of 1 dB [21,32,35]. Additional details on the ARM AMF2 instrumentation and associated uncertainties used in MARCUS campaign can be found in [19,21,22]. The CloudSat W-band CPR sensitivity was initially −30 dBZ [2,3,17] but degraded to −26 dBZ over time due to instrument aging [18]. This reduced sensitivity made it more difficult to detect weak clouds at greater distances, such as marine low clouds. The CloudSat hydrometeor detection algorithm is similar to the ARM algorithm developed by [57,58], with two modifications: a power probability weighting scheme and an along-track integration scheme [16]. Details of the CloudSat–CALIPSO and MARCUS radar cloud profile datasets, including cloud mask products and associated quality checks used to constrain cloud hydrometeors and remove background noise, are provided in [33].

The GV research flights conducted during the SOCRATES aircraft-based field campaign primarily targeted cold-sector MBL clouds, using in-cloud, below-cloud, and above-cloud transects to capture both time series and vertical profiles of cloud structure with a suite of in situ and remote sensing instruments. Airborne in situ probes, including the Cloud Droplet Probe (CDP) and Two-Dimensional Stereo Particle Imaging Probe (2D-S), were used to characterize cloud and drizzle microphysical properties during SOCRATES [37,38,40–42]. Additional details on the in situ probes, detection limits, and associated uncertainties are provided in [23,29].

Table A1. Summary of radar and in situ probe instrument measurements and uncertainties from three platforms.

Platform/Campaign	Instrument	Measurement and Uncertainties	References
Measurements of Aerosols, Radiation, and Clouds over the Southern Ocean (MARCUS)	Marine W-Band ARM Cloud Radar (M-WACR, 95 GHz)	Sensitivity: −50 dBZ (up to 20 dBZ) Cloud boundaries (H _{top} and H _{base}) and vertical resolution: 30 m. 2–4 dB systematical bias	[35,49]
CloudSat	Cloud Profile Radar (CPR, 94 GHz)	Sensitivity: −26 dBZ (up to 20 dBZ) Cloud boundaries and profile with vertical resolution: 240 m. Spatial resolution: 1.7 km × 1.4 km Version: P1_R05_E08_F03.hdf	[2,3,16,17]

Southern Ocean Cloud Radiation Aerosol Transport Experimental Study (SOCRATES)	Cloud Droplet Probe (CDP)	Signals attenuated at lower part of convective clouds, and below 1 km.	[37,38]
		Particle size distribution (PSD) and concentration of hydrometeors with a diameter between 2–50 μm .	
	Two-Dimensional, Stereo, Particle Imaging Probe (2D-S)	Cannot resolve non-spherical particles accurately.	[40–42]
		Size distribution and concentration of hydrometeors with a diameter between 10 to 1280 μm range. Cannot resolve for particle sizes $D < 40 \mu\text{m}$, also ice particle detection is certain only for $D > 200 \mu\text{m}$.	

Appendix B

Appendix B.1. Summary of the SOCRATES Airborne In Situ-Based Retrieval Framework Using Empirical Relationships Between Reflectivity and Cloud–Drizzle Microphysical Properties, and Associated Uncertainties

A cloud and drizzle microphysical property retrieval framework was developed in [29] using SOCRATES airborne in situ CDP and 2D-S probe measurements, in which empirical relationships were derived between radar reflectivity (Z) and microphysical properties for low-level clouds below 3 km. The method estimates effective radius (r_e) and liquid water content (LWC) for cloud and drizzle populations and forms the basis of the retrievals applied in this study. This appendix briefly summarizes the retrieval framework and their associated uncertainties, while detailed derivations and full sensitivity analyses are provided therein.

The CDP measures cloud droplets with diameters ranging from 2 to 50 μm . The 2D-S probe complements these observations by detecting larger drizzle particles, with reliable liquid particle detection above 40 μm and ice particle detection for diameters exceeding 200 μm . Particle sizes below 40 μm are subject to substantial uncertainty in the 2D-S measurements and were therefore excluded from the analysis [59,60]. Droplet size distributions obtained from the CDP and 2D-S probes were used to derive bulk in situ cloud and drizzle microphysical properties— r_e , LWC , N , and Z . These quantities were computed as continuous 1 Hz time series for each flight using diameter bins of 2–40 μm for cloud droplets and 40–1280 μm for drizzle particles. A threshold diameter of 40 μm was used to distinguish cloud droplets from drizzle particles [28,52].

Appendix B.2. Lognormal and Gamma Distribution Fits for CDP and 2D-S DSD Spectra

A lognormal distribution is used to represent the CDP DSD spectra for cloud particles between 2 and 40 μm , while a gamma distribution represents 2D-S drizzle DSD from 40 to 400 μm . The droplet number density spectrum, $N(D)$ ($\text{cm}^{-3} \mu\text{m}^{-1}$), represents the number of cloud or drizzle particles per unit volume within diameter interval $D \pm dD$, where dD is an infinitesimal increment in droplet diameter (μm). The lognormal distribution for CDP DSD spectra can be represented as:

$$N(D) = \frac{N}{\sigma_x \sqrt{2\pi}} \exp\left(-\frac{[\ln D - \ln D_0]^2}{2\sigma_x^2}\right), \quad (\text{A1})$$

where D is the cloud drop diameter (μm), D_0 is the modal diameter (μm), N is the droplet number concentration (in cm^{-3}), and σ_x is the logarithmic width of the distribution.

Similarly, the gamma distribution for 2D-S DSD spectra takes the following exponential form:

$$N(D) = N_0 D^\mu \exp(-\lambda D), \quad (\text{A2})$$

where D is the drizzle drop diameter (μm), N_0 ($\text{cm}^{-3} \mu\text{m}^{-1}$) is the intercept parameter, μ represents the shape parameter (μm^{-1}), and λ is the slope parameter of the distribution. The lognormal distribution for cloud DSD spectra (2–40 μm) shows a mode diameter (D_0) of 15 μm and a lognormal width (σ_x) of 0.4, while the gamma distribution for drizzle DSD spectra (40–400 μm) yields a shape parameter $\mu = 0.5$ and a slope parameter $\lambda = 0.13$.

The k th moment of droplet radius of the lognormal and gamma distribution from Equations (A1) and (A2) takes the form:

$$\langle r^k \rangle = N^{-1} \int r^k N(r) dr, \quad (\text{A3})$$

where r is the droplet radius, $r = D/2$ (μm). Additionally, the total droplet number concentration per unit volume (N , cm^{-3}) can be written as an integral of the number density per unit volume, $N(D)$, as follows:

$$N = \int N(D) \cdot dD = \int N(r) dr, \quad (\text{A4})$$

The cloud and drizzle DSDs can be used to calculate in situ Z (mm^6m^{-3}), LWC (gm^{-3}), and r_e (μm), using the following expressions [23]:

$$Z = \int_{D_{\min}}^{D_{\max}} N(D) D^6 dD, \quad (\text{A5})$$

$$LWC = \frac{\pi}{6} \rho_w \int_{D_{\min}}^{D_{\max}} N(D) D^3 dD, \quad (\text{A6})$$

$$r_e = \frac{\int_{D_{\min}}^{D_{\max}} r^3 N(D) dD}{\int_{D_{\min}}^{D_{\max}} r^2 N(D) dD}, \quad (\text{A7})$$

where ρ_w is the density of liquid water ($=10^6 \text{ gm}^{-3}$). As mentioned before, $D_{\min}$ and $D_{\max}$ is respectively defined as 2–40 μm for cloud droplets, and 40–400 μm for drizzle drops. Z is converted to logarithmic units (dBZ) using $\text{dBZ} = 10 \log(Z)$. Since the analysis is performed in logarithmic reflectivity space, Z is used throughout the paper to denote radar reflectivity in dBZ units.

The CDP and 2D-S probes operated simultaneously to provide independent measurements of cloud and drizzle droplets, respectively. Following [28], valid cloud profiles were defined by thresholds $LWC_c > 0.01 \text{ gm}^{-3}$ and $N_c > 5 \text{ cm}^{-3}$, while valid drizzle samples were identified by $N_d > 0.001 \text{ cm}^{-3}$. These criteria ensured adequate sampling and excluded clear-sky periods. Based on a Monte Carlo simulation with 100,000 iterations, propagated uncertainties in Z , r_e , and LWC were estimated from perturbations to the in situ DSD spectra using reported uncertainties in particle size and number concentration (30% and 20% for CDP; 20% and 50% for 2D-S). The resulting uncertainties in Z , r_e , and LWC are estimated at ~55% (50%), ~10% (10%), and ~23% (20%) for cloud (drizzle) droplets, respectively. These uncertainties primarily arise from sizing biases, detector response limitations, coincident particle counts, calibration uncertainties, and error propagation from particle size and concentration measurements.

Appendix B.3. Profiles of In Situ Cloud and Drizzle Droplet Spectra

A total of 87 cloud profiles and 50 drizzle profiles were constructed from 7329 CDP and 3564 2D-S in situ DSD spectra sampled at 1 Hz along continuous ascending and descending aircraft tracks (Figure A1). The selected profiles primarily represent uniform low-level stratocumulus MBL clouds below 3 km, which accounted for ~85% of SOCRA-TES cloud samples during the 15 research flights [23,33]. Cloud and drizzle microphysical profiles, including Z , LWC , and r_e , were calculated from the observed DSD spectra using Equations (A5)–(A7).

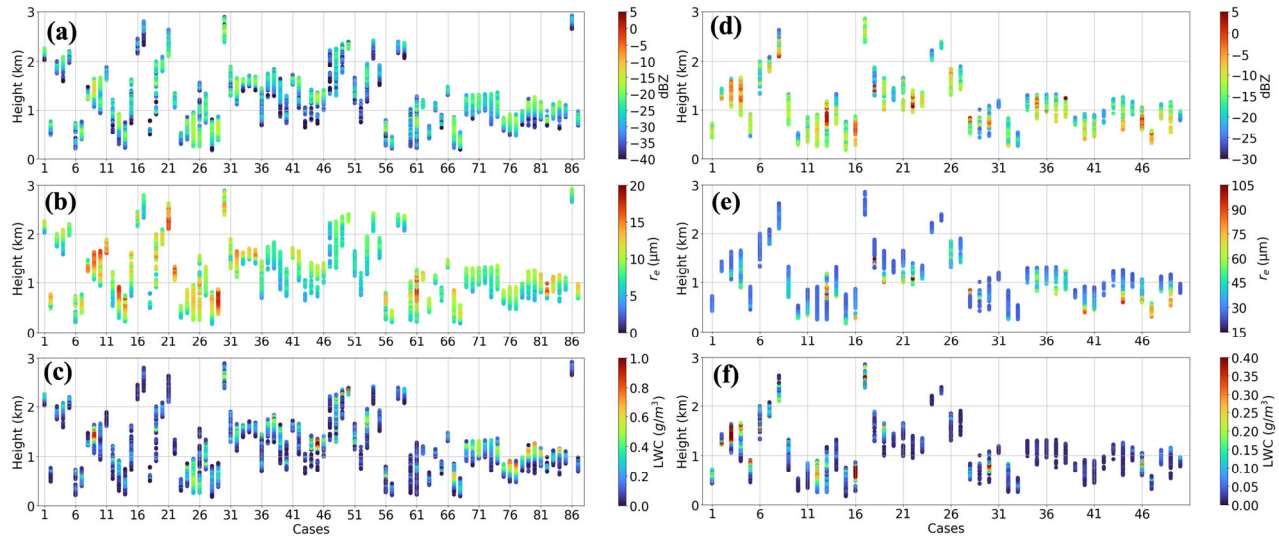


Figure A1. A total of 87 in-cloud profiles are constructed from 7329 in situ CDP cloud droplet spectra at 1 Hz from ascending and descending aircraft tracks during the SOCRATES to derive cloud (a) reflectivity profiles (Z_c , dBZ), (b) $r_{e,c}$ (μm) and (c) LWC_c (gm^{-3}). Panels (d–f) are the same as (a,b) except for the 50 profiles representing in situ 2D-S drizzle DSD spectra sampled at 1 Hz, showing (d) Z_d (dBZ), (e) $r_{e,d}$ (μm), and (f) LWC_d (gm^{-3}). Figure adapted from [29].

Appendix B.4. Empirical Coefficients for $r_{e,c}$ – Z and LWC_c – Z Relationships from In Situ-Measured Cloud and Drizzle DSDs and Their Sensitivities

Building on the formulations in [61,62], the cloud-droplet $r_{e,c}$ and LWC_c can be expressed as empirical relationships of the form below (see [29] for the full derivation):

$$r_{e,c} = \frac{\exp(3.912 - 0.5\sigma_x^2)}{N_c^{\frac{1}{6}}} \exp(0.0384Z_c), \text{ or}$$

$$r_{e,c} = a * \exp(0.0384Z_c), \text{ and} \quad (\text{A8})$$

$$LWC_c = \frac{\pi}{6} \exp(-4.5\sigma_x^2) N_c^{0.5} \exp(0.115Z_c), \text{ or}$$

$$LWC_c = b * \exp(0.115Z_c), \quad (\text{A9})$$

where Z_c is in dBZ, $r_{e,c}$ is in μm , N_c is in cm^{-3} , and LWC_c is in gm^{-3} . The $\log \sigma_x$ is set to 0.4, as observed from the lognormally fitted CDP DSD spectra.

Similarly, the drizzle $r_{e,d}$ and LWC_d can be expressed in the following forms, based on the gamma-fitted drizzle DSD:

$$r_{e,d} = \frac{50(\mu + 3)}{N_d^{\frac{1}{6}}} \left[\frac{\Gamma(\mu + 1)}{\Gamma(\mu + 7)} \right]^{\frac{1}{6}} \exp(0.0384Z_d), \text{ or}$$

$$r_{e,d} = c * \exp(0.0384Z_d), \text{ and} \quad (\text{A10})$$

$$LWC_d = \frac{\pi}{6} N_d^{0.5} \frac{\Gamma(\mu + 4)}{[\Gamma(\mu + 1)\Gamma(\mu + 7)]^{0.5}} \exp(0.115Z_d), \text{ or}$$

$$LWC_d = d * \exp(0.115Z_d), \quad (\text{A11})$$

The shape parameter μ governs the width and skewness of the gamma distribution and was set to 0.5 based on airborne in situ drizzle DSD observations in the 40–400 μm range.

The empirical r_e – Z and LWC – Z relationships for cloud and drizzle particles (Equations (A8)–(A11)) are governed by exponential functional forms, with coefficients that vary between profiles because of differences in droplet size distribution characteristics influenced by factors such as CCN properties, updraft velocity, and water vapor supersaturation [62]. The empirical coefficients were derived from best-fit relationships using kernel density estimation and linear regression applied to high sample-density regions in the log-transformed r_e – Z and LWC – Z spaces (Figure 7 of [29]). The resulting coefficients are $a = 23.02 \pm 2.4$ and $b = 2.70 \pm 0.95$ for clouds, and $c = 49.81 \pm 3.52$ and $d = 0.15 \pm 0.11$ for drizzle.

The sensitivities of the empirical coefficients a , b , c , and d to the underlying DSD distribution parameters and number concentrations are discussed (Figures 5 and 6 of [29]). CDP-measured N_c ranges from 0 to 200 cm^{-3} , with a mean of $\sim 90 \text{ cm}^{-3}$. With N_c fixed at 90 cm^{-3} , $r_{e,c}$ increases with reflectivity from 4 to 7.1 μm between -45 and -30 dBZ, and to 13.6 μm at -15 dBZ. Coefficient a varies from 19.4 to 26.2, changing by $\sim 4\%$ for a ± 0.1 shift in σ_x (centered at 0.4) and $\sim 8\%$ for a $\pm 30 \text{ cm}^{-3}$ shift in N_c (centered at 90 cm^{-3}). Similarly, LWC_c increases with reflectivity, while coefficient b ranges from 1 to 4.7, varying by $\sim 26\%$ with ± 0.1 changes in σ_x and $\sim 23\%$ with $\pm 30 \text{ cm}^{-3}$ changes in N_c . For drizzle, 2D-S retrieved N_d ranges from 0 to 10 cm^{-3} , with a mean of $\sim 1 \text{ cm}^{-3}$. Effective radius $r_{e,d}$ rises from 25 to 33 μm between -20 and -10 dBZ and to 52 μm at 0 dBZ. Coefficient c shows limited sensitivity, ranging from 45.2 to 53.2, with $\sim 3\%$ variation for a ± 0.3 change in μ (centered at 0.5) and $\sim 4\%$ for a $\pm 0.2 \text{ cm}^{-3}$ change in N_d (centered at 1 cm^{-3}). Likewise, coefficient d varies between $\sim 13\%$ and $\sim 6\%$ for the same shift in μ and N_d .

Appendix C

Appendix C.1. Estimating Cloud Boundaries from CloudSat CPR Reflectivity Profiles Following [23]

The lack of dedicated H_{base} and H_{top} height products in CloudSat CPR detected cloud profiles complicates the separation of cloud and drizzle reflectivity. H_{top} was defined as the highest altitude with a detectable CPR reflectivity signal (dBZ > -26), while H_{base} was estimated using a stepwise technique after classifying profiles as drizzling or non-drizzling. In situ CDP and 2D-S measurements indicate reflectivity ranges of -50 to -11 dBZ for clouds and -26 to 10 dBZ for drizzle, with cloud droplets rarely exceeding -15 dBZ. Following [45], profiles were therefore labeled as drizzling if reflectivity exceeded -15 dBZ anywhere in the column, noting that SO drizzle may occur in both liquid and ice phases [22].

For non-drizzling cases (reflectivity < -15 dBZ throughout the cloud vertical column), H_{base} was defined as the lowest altitude with a valid radar return. In drizzling cases, reflectivity above H_{base} includes both cloud and drizzle contributions, while below H_{base} it reflects precipitation only. Near the cloud base, collision–coalescence produces larger particles, leading to sharp increases in reflectivity, Doppler velocity, and spectral width, which indicate turbulence and drizzle onset. Accordingly, H_{base} was identified where dBZ exhibited marked increases, i.e., the local maxima in dBZ gradients. For strong precipitation (dBZ > 5 near the surface; [63]), H_{base} was estimated from the vertical dBZ gradient above this level. This approach provides a reasonable approximation of H_{base} in the absence of ceilometer or radiosonde-derived cloud-base products for CPR. As discussed, CloudSat CPR signals are subject to near-surface attenuation and surface clutter [33], while reliable cloud detection is generally limited to heights above ~ 500 m, making ~ 500 m the lowest usable cloud detection height.

Appendix C.2. Segregating Cloud and Drizzle Reflectivity Profiles

The method presented in [45] to segregate radar reflectivity into cloud and drizzle components was applied to MARCUS M-WACR and CloudSat CPR measurements. Using a reflectivity threshold of -15 dBZ, cloud droplets (<-15 dBZ) were separated from drizzle drops (>-15 dBZ). Assuming a vertically constant cloud droplet N_c , LWC_c increases linearly with height. Radar reflectivity just above H_{base} contains contributions from both cloud droplets and drizzle, whereas below the cloud base, it reflects only drizzle. Therefore, cloud reflectivity at the H_{base} was estimated by subtracting the reflectivity one range gate below H_{base} from the total radar reflectivity, assuming drizzle contributions are consistent across the H_{base} (Figure 2b from [45]).

If the total reflectivity one range gate below H_{base} is smaller than that at the base, the retrieval assigns the minimum detectable reflectivity (~ -50 dBZ for M-WACR and ~ -26 for CPR) as the reflectivity at H_{base} . Using this as a baseline, the cloud reflectivity profile within the layer was estimated by linear interpolation from the cloud base to the lower of the -15 dBZ height level and H_{top} . Above the -15 dBZ height level (i.e., the height where reflectivity reaches -15 dBZ), the profile is treated as entirely cloud. Finally, the drizzle reflectivity profile within the cloud layer is obtained by subtracting the cloud reflectivity profile from the M-WACR (and/or CPR) total reflectivity (cloud + drizzle) between the cloud base and the height where reflectivity reaches -15 dBZ. The -15 dBZ level represents the upper interpolation limit used to estimate the cloud reflectivity profile and corresponds to the “precipitation-top” within the cloud layer rather than a fixed cloud–drizzle separation threshold, since drizzle reflectivity may also occur below -15 dBZ in the in situ observations. H_{top} is determined independently from the cloud radar reflectivity and therefore should always be greater than or at least equal to the precipitation-top height but cannot be lower. The true cloud base may in some cases lie above the selected value due to the accumulation of large droplets near the cloud base. Consequently, both boundary-selection methods may yield cloud thicknesses that are thinner than the actual extent [21]. Figure A2 illustrates a CloudSat CPR reflectivity vertical profile with estimated cloud boundaries and segregated cloud and drizzle reflectivities.

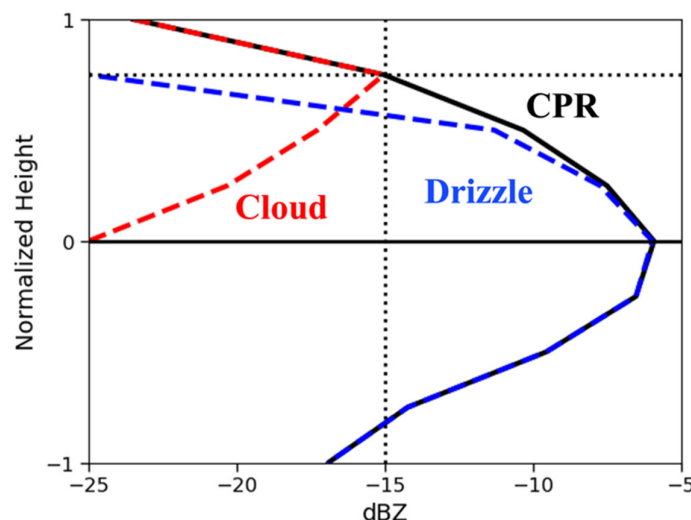


Figure A2. Separation of cloud (red) and drizzle (blue) reflectivity within a CPR-detected cloud layer. The black curve denotes CPR-measured reflectivity. Labels -1 , 0 , and 1 correspond to drizzle (or layer) base, estimated cloud base, and cloud top heights, respectively. Vertical and horizontal dashed lines indicate the location and altitude of the -15 dBZ reflectivity threshold. The same method was applied to decompose MARCUS M-WACR reflectivity profiles into cloud and drizzle

reflectivities, except that dedicated cloud-base heights from Ceilometer/MPL measurements were available for the MARCUS dataset.

References

1. Dong, X.; Minnis, P. Stratus, Stratocumulus, and Remote Sensing. In *Fast Processes in Large-Scale Atmospheric Models*; Geophysical Monograph Series; Wiley: Hoboken, NJ, USA, 2023; pp. 141–199. <https://doi.org/10.1002/9781119529019.ch6>.
2. Stephens, G.L.; Vane, D.G.; Boain, R.J.; Mace, G.G.; Sassen, K.; Wang, Z.; Illingworth, A.J.; O'Connor, E.J.; Rossow, W.B.; Durden, S.L. The CloudSat mission and the A-Train: A new dimension of space-based observations of clouds and precipitation. *Bull. Am. Meteorol. Soc.* **2002**, *83*, 1771–1790. <https://doi.org/10.1175/BAMS-83-12-1771>.
3. Stephens, G.L.; Vane, D.G.; Tanelli, S.; Im, E.; Durden, S.; Rokey, M.; Reinke, D.; Partain, P.; Mace, G.G.; Austin, R. CloudSat mission: Performance and early science after the first year of operation. *J. Geophys. Res.* **2008**, *113*, D00A18. <https://doi.org/10.1029/2008JD009982>.
4. Bodas-Salcedo, A.; Hill, P.G.; Furtado, K.; Williams, K.D.; Field, P.R.; Manners, J.C.; Hyder, P.; Kato, S. Large contribution of supercooled liquid clouds to the solar radiation budget of the Southern Ocean. *J. Clim.* **2016**, *29*, 4213–4228. <https://doi.org/10.1175/JCLI-D-15-0564.1>.
5. Hu, Y.; Rodier, S.; Xu, K.; Sun, W.; Huang, J.; Lin, B.; Zhai, P.; Josset, D. Occurrence, liquid water content, and fraction of supercooled water clouds from combined CALIOP/IIR/MODIS measurements. *J. Geophys. Res.* **2010**, *115*, D00H34. <https://doi.org/10.1029/2009JD012384>.
6. Dong, X.; Xi, B.; Kennedy, A.; Minnis, P.; Wood, R. A 19-month record of marine aerosol-cloud-radiation properties derived from DOE ARM mobile facility deployment at the Azores. Part I: Cloud fraction and single-layered MBL cloud properties. *J. Clim.* **2014**, *27*, 3665–3682. <https://doi.org/10.1175/JCLI-D-13-00553.1>.
7. Wu, P.; Dong, X.; Xi, B. A climatology of marine boundary layer cloud and drizzle properties derived from ground-based observations over the Azores. *J. Clim.* **2020**, *33*, 10133–10148. <https://doi.org/10.1175/JCLI-D-20-0272.1>.
8. Qiu, S.; Dong, X.; Xi, B.; Li, J.-L.F. Characterizing Arctic mixed-phase cloud structure and its relationship with humidity and temperature inversion using ARM NSA observations. *J. Geophys. Res. Atmos.* **2015**, *120*, 7737–7746. <https://doi.org/10.1002/2014JD023022>.
9. Järvinen, E.; Nehlert, F.; Xu, G.; Waitz, F.; Mioche, G.; Dupuy, R.; Jourdan, O.; Schnaiter, M. Investigating the vertical extent and short-wave radiative effects of the ice phase in Arctic summertime low-level clouds. *Atmos. Chem. Phys.* **2023**, *23*, 7611–7633. <https://doi.org/10.5194/acp-23-7611-2023>.
10. McCoy, I.L.; McCoy, D.T.; Wood, R.; Regayre, L.; Watson-Parris, D.; Grosvenor, D.P. The hemispheric contrast in cloud microphysical properties constrains aerosol forcing. *Proc. Natl. Acad. Sci. USA* **2020**, *117*, 18998–19006. <https://doi.org/10.1073/pnas.1922502117>.
11. McCoy, I.L.; Bretherton, C.S.; Wood, R.; Twohy, C.H.; Gettelman, A.; Bardeen, C.G.; Toohey, D.W. Influences of recent particle formation on Southern Ocean aerosol variability and low cloud properties. *J. Geophys. Res. Atmos.* **2021**, *126*, e2020JD033529. <https://doi.org/10.1029/2020JD033529>.
12. Dong, X.; Wu, P.; Wang, Y.; Xi, B.; Huang, Y. New observational constraints on warm rain processes and their climate implications. *Geophys. Res. Lett.* **2021**, *48*, e2020GL091836. <https://doi.org/10.1029/2020GL091836>.
13. Brendecke, J.; Dong, X.; Xi, B.; Wu, P. Maritime cloud and drizzle microphysical properties retrieved from ship-based observations during MAGIC. *Earth Space Sci.* **2021**, *8*, e2020EA001588. <https://doi.org/10.1029/2020EA001588>.
14. Mace, G.G.; Zhang, Q. The CloudSat radar-lidar geometrical profile product (RL-GeoProf): Updates, improvements, and selected results. *J. Geophys. Res. Atmos.* **2014**, *119*, 9441–9462. <https://doi.org/10.1002/2013JD021374>.
15. Winker, D.M.; Vaughan, M.A.; Omar, A.; Hu, Y.; Powell, K.A.; Liu, Z.; Hunt, W.H.; Young, S.A. Overview of the CALIPSO mission and CALIOP data processing algorithms. *J. Atmos. Ocean. Technol.* **2009**, *26*, 2310–2323. <https://doi.org/10.1175/2009JTECHA1281.1>.
16. Marchand, R.; Mace, G.G.; Ackerman, T.; Stephens, G. Hydrometeor detection using CloudSat—An Earth-orbiting 94-GHz cloud radar. *J. Atmos. Ocean. Technol.* **2008**, *25*, 519–533. <https://doi.org/10.1175/2007JTECHA1006.1>.
17. Tanelli, S.; Durden, S.L.; Im, E.; Pak, K.S.; Reinke, D.G.; Partain, P.; Haynes, J.M.; Marchand, R.T. CloudSat's cloud profiling radar after two years in orbit: Performance, calibration, and processing. *IEEE Trans. Geosci. Remote Sens.* **2008**, *46*, 3560–3573. <https://doi.org/10.1109/TGRS.2008.2002030>.

18. Lebsock, M.D.; L'Ecuyer, T.S.; Wood, N.B.; Haynes, J.M.; Smalley, M.A. Status of the CloudSat mission. In *Satellite Precipitation Measurement*; Levizzani, V., Kidd, C., Kirschbaum, D.B., Kummerow, C.D., Nakamura, K., Turk, F.J., Eds.; Springer: Cham, Switzerland, 2020; Volume 67. https://doi.org/10.1007/978-3-030-24568-9_2.
19. McFarquhar, G.M.; Bretherton, C.S.; Marchand, R.; Protat, A.; DeMott, P.J.; Alexander, S.P.; Roberts, G.C.; Twohy, C.H.; Toohey, D.; Siems, S.; et al. Observations of clouds, aerosols, precipitation, and surface radiation over the Southern Ocean: An overview of CAPRICORN, MARCUS, MICRE, and SOCRATES. *Bull. Am. Meteorol. Soc.* **2021**, *102*, E894–E928. <https://doi.org/10.1175/BAMS-D-20-0132.1>.
20. Mace, G.G.; Protat, A.; Humphries, R.S.; Alexander, S.P.; McRobert, I.M.; Ward, J.; Selleck, P.; Keywood, M.; McFarquhar, G.M. Southern Ocean cloud properties derived from CAPRICORN and MARCUS data. *J. Geophys. Res. Atmos.* **2021**, *126*, e2020JD033368. <https://doi.org/10.1029/2020JD033368>.
21. Marcovecchio, A.R.; Xi, B.; Zheng, X.; Wu, P.; Dong, X.; Behrangi, A. What are the similarities and differences in marine boundary layer cloud and drizzle microphysical properties during the ACE-ENA and MARCUS field campaigns? *J. Geophys. Res. Atmos.* **2023**, *128*, e2022JD037109. <https://doi.org/10.1029/2022JD037109>.
22. Xi, B.; Dong, X.; Zheng, X.; Wu, P. Cloud phase and macrophysical properties over the Southern Ocean during the MARCUS field campaign. *Atmos. Meas. Tech.* **2022**, *15*, 3761–3777. <https://doi.org/10.5194/amt-15-3761-2022>.
23. Das, A.; Xi, B.; Zheng, X.; Dong, X. Marine boundary layer cloud boundaries and phase estimation using airborne radar and in situ measurements during the SOCRATES campaign over Southern Ocean. *Atmosphere* **2025**, *16*, 1195. <https://doi.org/10.3390/atmos16101195>.
24. DeMott, P.J.; Hill, T.C.J.; McFarquhar, G. Measurements of Aerosol Radiation and Clouds over the Southern Ocean (MARCUS): Ice nucleating particle measurements field campaign report. In *U.S. Department of Energy Report*; DOE/SC-ARM-18-031; U.S. Department of Energy: Washington, DC, USA, 2018; 12p. Available online: <https://www.osti.gov/servlets/purl/1489372> (accessed on 14 January 2026).
25. Hu, Y.; Geerts, B.; Deng, M.; Grasmick, C.; Wang, Y.; Lackner, C.P.; Hu, Y.; Lebo, Z.J.; Zhang, D. Vertical structure and ice production processes of shallow convective postfrontal clouds over the Southern Ocean in MARCUS. Part I: Observational study. *J. Atmos. Sci.* **2023**, *80*, 1285–1306. <https://doi.org/10.1175/JAS-D-21-0243.1>.
26. D'Alessandro, J.J.; McFarquhar, G.M.; Wu, W.; Stith, J.L.; Jensen, J.B.; Rauber, R.M. Characterizing the occurrence and spatial heterogeneity of liquid, ice and mixed phase low-level clouds over the Southern Ocean using in situ observations acquired during SOCRATES. *J. Geophys. Res. Atmos.* **2021**, *126*, e2020JD034482. <https://doi.org/10.1029/2020JD034482>.
27. Romatschke, U.; Vivekanandan, J. Cloud and precipitation particle identification using cloud radar and lidar measurements: Retrieval technique and validation. *Earth Space Sci.* **2022**, *9*, e2022EA002299. <https://doi.org/10.1029/2022EA002299>.
28. Zheng, X.; Dong, X.; Xi, B.; Logan, T.; Wang, Y. Distinctive aerosol-cloud-precipitation interactions in marine boundary layer clouds from the ACE-ENA and SOCRATES aircraft field campaigns. *Atmos. Chem. Phys.* **2024**, *24*, 10323–10347. <https://doi.org/10.5194/acp-24-10323-2024>.
29. Das, A.; Dong, X.; Xi, B. Deriving empirical relationships between MBL cloud microphysical properties and radar reflectivity using airborne in situ measurements over the Southern Ocean. *J. Atmos. Ocean. Technol.* **2026**, *43*, 425–443. <https://doi.org/10.1175/JTECH-D-25-0069.1>.
30. Yuan, J.; Houze, R.A.; Heymsfield, A.J. Vertical structures of anvil clouds of tropical mesoscale convective systems observed by CloudSat. *J. Atmos. Sci.* **2011**, *68*, 1653–1674. <https://doi.org/10.1175/2011JAS3687.1>.
31. Leon, D.C.; Wang, Z.; Liu, D. Climatology of drizzle in marine boundary layer clouds based on 1 year of data from CloudSat and Cloud-Aerosol Lidar and Infrared Pathfinder Satellite Observations (CALIPSO). *J. Geophys. Res.* **2008**, *113*, D00A14. <https://doi.org/10.1029/2008JD009835>.
32. Tansey, E.; Marchand, R.; Protat, A.; Alexander, S.P.; Ding, S. Southern Ocean precipitation characteristics observed from CloudSat and ground instrumentation during the Macquarie Island Cloud and Radiation Experiment (MICRE): April 2016 to March 2017. *J. Geophys. Res. Atmos.* **2022**, *127*, e2021JD035370. <https://doi.org/10.1029/2021JD035370>.
33. Dong, X.; Das, A.; Xi, B.; Zheng, X.; Behrangi, A.; Marcovecchio, A.R.; Girone, D.J. Quantifying the differences in Southern Ocean clouds observed by radar and lidar from three platforms. *Geophys. Res. Lett.* **2025**, *52*, e2024GL112079. <https://doi.org/10.1029/2024GL112079>.
34. Marcovecchio, A.R.; Xi, B.; Zheng, X.; Wu, P.; Dong, X.; Behrangi, A. Data from “What are the Similarities and Differences in Marine Boundary Layer Cloud and Drizzle Microphysical Properties During the ACE-ENA and MARCUS Field Campaigns?”; University of Arizona Research Data Repository: Tucson, AZ, USA, 2023. <https://doi.org/10.25422/azu.data.23748969.v1>.

35. Kollias, P.; Clothiaux, E.E.; Ackerman, T.P.; Albrecht, B.A.; Widener, K.B.; Moran, K.P.; Luke, E.P.; Johnson, K.L.; Bharadwaj, N.; Mead, J.B.; et al. Development and applications of ARM millimeter-wavelength cloud radars. *Meteor. Monogr.* **2016**, *57*, 17.1–17.19. <https://doi.org/10.1175/AMSMONOGRAPHIS-D-15-0037.1>.
36. ARM Data Center. *Atmospheric Radiation Measurement (ARM) User Facility. W-band Cloud Radar Active Remote Sensing of Cloud (ARSCLWACR1KOLLIAS), 2017-10-29 to 2018-03-24, ARM Mobile Facility (MAR) Hobart, AUS to Antarctic Coast—Resupply Ship Aurora Australis; AMF2 (M1); Deng, M.; Clothiaux, E.; Kollias, P., Eds.; ARM Data Center: Oak Ridge, TN, USA, 2017.* <https://doi.org/10.5439/1987455>.
37. Lance, S.; Brock, C.A.; Rogers, D.; Gordon, J.A. Water droplet calibration of the Cloud Droplet Probe (CDP) and in-flight performance in liquid, ice and mixed-phase clouds during ARCPAC. *Atmos. Meas. Tech.* **2010**, *3*, 1683–1706. <https://doi.org/10.5194/amt-3-1683-2010>.
38. Faber, S.; French, J.R.; Jackson, R. Laboratory and in-flight evaluation of measurement uncertainties from a commercial Cloud Droplet Probe (CDP). *Atmos. Meas. Tech.* **2018**, *11*, 3645–3659. <https://doi.org/10.5194/amt-11-3645-2018>.
39. NSF NCAR Earth Observing Laboratory. *SOCRATES: Low Rate (LRT—1 sps) Navigation, State Parameter, and Microphysics Flight-Level Data, Version 1.4*; NSF NCAR Earth Observing Laboratory: Boulder, CO, USA; 2022. <https://doi.org/10.5065/D6M32TM9>.
40. Lawson, R.P.; O'Connor, D.; Zmarzly, P.; Weaver, K.; Baker, B.; Mo, Q.; Jonsson, H. The 2D-S (Stereo) Probe: Design and preliminary tests of a new airborne, high-speed, high-resolution particle imaging probe. *J. Atmos. Ocean. Technol.* **2006**, *23*, 1462–1477. <https://doi.org/10.1175/JTECH1927.1>.
41. Baker, B.; Mo, Q.; Lawson, R.P.; O'Connor, D.; Korolev, A. Drop size distributions and the lack of small drops in RICO rain shafts. *J. Appl. Meteor. Climatol.* **2009**, *48*, 616–623. <https://doi.org/10.1175/2008JAMC1934.1>.
42. Wu, W.; McFarquhar, G.M. On the impacts of different definitions of maximum dimension for nonspherical particles recorded by 2D imaging probes. *J. Atmos. Ocean. Technol.* **2016**, *33*, 1057–1072. <https://doi.org/10.1175/JTECH-D-15-0177.1>.
43. Wu, W.; McFarquhar, G.M. *NSF/NCAR GV HIAPER 2D-S Particle Size Distribution (PSD) Product Data, Version 1.1*; NSF NCAR Earth Observing Laboratory: Boulder, CO, USA, 2019. <https://doi.org/10.26023/8HMG-WQP3-XA0X>.
44. Rogers, R.R.; Yau, M.K. *A Short Course in Cloud Physics*, 3rd ed.; Butterworth-Heinemann: Oxford, UK, **1996**; 291p.
45. Wu, P.; Dong, X.; Xi, B.; Tian, J.; Ward, D.M. Profiles of MBL cloud and drizzle microphysical properties retrieved from ground-based observations and validated by aircraft in situ measurements over the Azores. *J. Geophys. Res. Atmos.* **2020**, *125*, e2019JD032205. <https://doi.org/10.1029/2019JD032205>.
46. Kollias, P.; Puigdomènech Treserras, B.; Protat, A. Calibration of the 2007–2017 record of Atmospheric Radiation Measurements cloud radar observations using CloudSat. *Atmos. Meas. Tech.* **2019**, *12*, 4949–4964. <https://doi.org/10.5194/amt-12-4949-2019>.
47. Toto, T. *Interpolated Sounding and Gridded Sounding Value-Added Products*; Brookhaven National Laboratory: New York, NY, USA, 2016. <https://doi.org/10.2172/1326751>.
48. Cadetdu, M.P.; Liljegren, J.C.; Turner, D.D. The Atmospheric Radiation Measurement (ARM) program network of microwave radiometers: Instrumentation, data, and retrievals. *Atmos. Meas. Tech.* **2013**, *6*, 2359–2372. <https://doi.org/10.5194/amt-6-2359-2013>.
49. ARM Data Center. *Atmospheric Radiation Measurement (ARM) User Facility. MWR Retrievals (MWRRET1LILJCLOU), 2017-10-21 to 2018-03-23, ARM Mobile Facility (MAR) Hobart, AUS to Antarctic Coast—Resupply Ship Aurora Australis; AMF2 (M1); Zhang, D., Ed.; ARM Data Center: Oak Ridge, TN, USA, 2017.* <https://doi.org/10.5439/1027369>.
50. Wu, P.; Dong, X.; Xi, B. Marine boundary layer drizzle properties and their impact on cloud property retrieval. *Atmos. Meas. Tech.* **2015**, *8*, 3555–3562. <https://doi.org/10.5194/amt-8-3555-2015>.
51. Fielding, M.D.; Chiu, J.C.; Hogan, R.J.; Feingold, G.; Eloranta, E.; O'Connor, E.J.; Cadetdu, M.P. Joint retrievals of cloud and drizzle in marine boundary layer clouds using ground-based radar, lidar and zenith radiances. *Atmos. Meas. Tech.* **2015**, *8*, 2663–2683. <https://doi.org/10.5194/amt-8-2663-2015>.
52. Wood, R. Drizzle in stratiform boundary layer clouds. Part I: Vertical and horizontal structure. *J. Atmos. Sci.* **2005**, *62*, 3011–3033. <https://doi.org/10.1175/JAS3529.1>.
53. Austin, R.T.; Heymsfield, A.J.; Stephens, G.L. Retrieval of ice cloud microphysical parameters using the CloudSat millimeter-wave radar and temperature. *J. Geophys. Res.* **2009**, *114*, D00A23. <https://doi.org/10.1029/2008JD010049>.
54. Wu, P.; Dong, X.; Xi, B.; Liu, Y.; Thieman, M.; Minnis, P. Effects of environment forcing on marine boundary layer cloud-drizzle processes. *J. Geophys. Res. Atmos.* **2017**, *122*, 4463–4478. <https://doi.org/10.1002/2016JD026326>.
55. Romatschke, U.; Dixon, M.; Tsai, P.; Loew, E.; Vivekanandan, J.; Emmett, J.; Rilling, R. The NCAR airborne 94-GHz cloud radar: Calibration and data processing. *Data* **2021**, *6*, 66. <https://doi.org/10.3390/data6060066>.

56. Schwartz, M.C.; Ghate, V.P.; Albrecht, B.A.; Zuidema, P.; Cadeddu, M.P.; Vivekanandan, J.; Ellis, S.M.; Tsai, P.; Eloranta, E.W.; Mohrmann, J.; et al. Merged cloud and precipitation dataset from the HIAPER GV for the Cloud System Evolution in the Trades (CSET) campaign. *J. Atmos. Ocean. Technol.* **2019**, *36*, 921–940. <https://doi.org/10.1175/JTECH-D-18-0111.1>.
57. Clothiaux, E.E.; Miller, M.A.; Albrecht, B.A.; Ackerman, T.P.; Verlinde, J.; Babb, D.M.; Peters, R.M.; Syrett, W.J. An evaluation of a 94-GHz radar for remote sensing of cloud properties. *J. Atmos. Ocean. Technol.* **1995**, *12*, 201–229. [https://doi.org/10.1175/1520-0426\(1995\)012<0201:AEOAGR>2.0.CO;2](https://doi.org/10.1175/1520-0426(1995)012<0201:AEOAGR>2.0.CO;2).
58. Clothiaux, E.E.; Ackerman, T.P.; Mace, G.G.; Moran, K.P.; Marchand, R.T.; Miller, M.A.; Martner, B.E. Objective determination of cloud heights and radar reflectivities using a combination of active remote sensors at the ARM CART sites. *J. Appl. Meteor. Climatol.* **2000**, *39*, 645–665. [https://doi.org/10.1175/1520-0450\(2000\)039<0645:ODOCHA>2.0.CO;2](https://doi.org/10.1175/1520-0450(2000)039<0645:ODOCHA>2.0.CO;2).
59. Baumgardner, D.; Korolev, A. Airspeed corrections for optical array probe sample volumes. *J. Atmos. Ocean. Technol.* **1997**, *14*, 1224–1229. [https://doi.org/10.1175/1520-0426\(1997\)014<1224:ACFOAP>2.0.CO;2](https://doi.org/10.1175/1520-0426(1997)014<1224:ACFOAP>2.0.CO;2).
60. Wang, Y.; Zhao, C.; McFarquhar, G.M.; Wu, W.; Reeves, M.; Li, J. Dispersion of droplet size distributions in supercooled non-precipitating stratocumulus from aircraft observations obtained during the Southern Ocean Cloud Radiation Aerosol Transport Experimental Study. *J. Geophys. Res. Atmos.* **2021**, *126*, e2020JD033720. <https://doi.org/10.1029/2020JD033720>.
61. Frisch, A.S.; Fairall, C.W.; Snider, J.B. Measurement of stratus cloud and drizzle parameters in ASTEX with a K α -band Doppler radar and a microwave radiometer. *J. Atmos. Sci.* **1995**, *52*, 2788–2799. [https://doi.org/10.1175/1520-0469\(1995\)052<2788:MOS-CAD>2.0.CO;2](https://doi.org/10.1175/1520-0469(1995)052<2788:MOS-CAD>2.0.CO;2).
62. Dong, X.; Mace, G.G. Profiles of low-level stratus cloud microphysics deduced from ground-based measurements. *J. Atmos. Ocean. Technol.* **2003**, *20*, 42–53. [https://doi.org/10.1175/1520-0426\(2003\)020<0042:POLLSC>2.0.CO;2](https://doi.org/10.1175/1520-0426(2003)020<0042:POLLSC>2.0.CO;2).
63. Shupe, M.D. A ground-based multisensor cloud phase classifier. *Geophys. Res. Lett.* **2007**, *34*, L22809. <https://doi.org/10.1029/2007GL031008>.

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