



1 **Cloud phase estimation and macrophysical properties of low-level clouds using in-situ and radar**
2 **measurements over the Southern Ocean during the SOCRATES campaign**

3
4 Anik Das¹, Baike Xi¹, Xiaojian Zheng², and Xiquan Dong^{1*}

5
6 ¹Department of Hydrology and Atmospheric Sciences, University of Arizona, Tucson, AZ, USA

7
8 ²Environmental Science Division, Argonne National Laboratory, Lemont, IL, USA

9 **Correspondence:** Xiquan Dong (xdong@arizona.edu)

10 **Abstract.** The Southern Ocean (SO) provides a unique natural laboratory for studying cloud formation
11 and cloud-aerosol interactions with minimal anthropogenic influence. The Southern Ocean Clouds,
12 Radiation, Aerosol Transport Experimental Study (SOCRATES), was an aircraft-based campaign
13 conducted from January 15 to February 28, 2018, off the coast of Hobart, Tasmania. During
14 SOCRATES, the NSF/NCAR GV research aircraft, equipped with in-situ probes and remote sensors,
15 observed aerosol, cloud and precipitation properties, and provided detailed vertical structure of clouds
16 over the SO, particularly for the low-level clouds (below 3 km). The HIAPER Cloud Radar (HCR) and
17 in-situ cloud and drizzle probes (CDP and 2DS) measurements were used to provide comprehensive
18 statistical and phase-relevant macrophysical properties for the low-level clouds sampled by the 15
19 research flights during SOCRATES. A new method based on HCR reflectivity and spectrum width
20 gradient was developed to estimate cloud boundaries (cloud-base and -top heights) and classify cloud
21 types based on their top and base heights. Low-level clouds were found to be the most prevalent, with
22 an almost 90% occurrence frequency. A new phase determination method was also developed to
23 identify the single-layered low-level clouds as liquid, ice, and mixed-phases, with occurrence
24 frequencies of 45.4%, 32.5%, and 22.2%, respectively. Low-level clouds over the SO have significantly
25 higher SLW concentrations, with liquid being most prevalent at higher temperatures, ice phase
26 dominating at lower temperatures, and mixed phase being least common due to its thermodynamic
27 instability. Regarding their vertical distributions, the liquid phase occurs most frequently in the lower
28 mid-cloud range (from 500 m to 1 km), the mixed phase dominates at cloud bases lower than 1 km but
29 is well distributed along the vertical cloud layer, while the ice phase is prevalent from the middle to
30 upper cloud levels (1-3 km). The higher occurrence of the mixed phase at the cloud base could be
31 attributed to large drizzle-sized drops and/or ice particles.

32 **1 Introduction**

33 Southern Ocean (SO) clouds impact the radiation budget over the region in a significant manner (Kay
34 et al., 2012; McCoy et al., 2014) which the global climate models cannot simulate accurately (Bodas-
35 Salcedo et al., 2016; Cesana & Chepfer, 2013; Kay et al., 2016; Trenberth & Fasullo, 2010; Wang et
36 al., 2018), which tends to underestimate the shortwave fluxes, also producing lower cloud fraction and
37 less supercooled liquid water than observed (D'Alessandro et al. 2021). The SO represents a remote,
38 pristine, and pre-industrial environment (Hamilton et al., 2014; Uetake et al., 2020; Humphries et al.,
39 2021) and provides a unique natural laboratory to understand cloud formation and microphysical
40 properties, cloud-aerosol interactions with minimal anthropogenic influences (McCoy et al., 2015; Xi
41 et al., 2022).

42 The low-level SO clouds feature a predominantly high concentration of supercooled liquid water
43 (SLW, almost 80% of low-level clouds contain SLW over a temperature range of -40 to 0°C, Hu et al.,
44 2010). Their cloud macrophysical and microphysical properties are different from subtropical marine
45 boundary layer (MBL) clouds which contain almost all liquid clouds (Dong et al., 2014; Wu et al.,
46 2020; Zhao et al., 2020) and from the Arctic mixed-phase clouds with a top layer of liquid and bottom
47 layer of ice clouds (Qiu et al., 2015). Understanding the dominant cloud phase and phase-related spatial
48 homogeneity of the low-level SO clouds is crucial to expanding our current understanding of the region
49 along with developing better parametrization for the increased accuracy of the global climate model



50 predictions (Zhao et al, 2023; Liu et al 2023; etc.). Identifying the cloud phase is crucial to accurately
51 retrieving cloud macrophysical and microphysical properties because most algorithms are tuned for
52 specific cloud phases over different climatic regions (Shupe, 2007). Incorrect parametrization of low-
53 level clouds is a key climate uncertainty and bias; and causes wide intermodel variation (~50%) (Klein
54 et al., 2017) as liquid-to-ice conversion of cloud particles reduces albedo at the top of the atmosphere
55 (TOA) (Xi et al., 2022).

56 Several studies exist on classifying cloud-type, cloud phase and hydrometeor-type detection over
57 the SO region (e.g., Xi et al., 2022; Desai et al., 2023; D'Alessandro et al., 2021, 2019; Romatschke &
58 Vivekanandan., 2023; Atlas et al., 2021; Schima et al., 2022; Zaremba et al., 2020) and Arctic clouds
59 (e.g. Shupe 2007; Korelov & Milbrandt, 2022). They utilized a suite of in-situ, radar-lidar and machine-
60 learning approaches to predict cloud phase or cloud-hydrometeor types along with their relevant macro-
61 and micro-physical properties but reported a significant difference in phase retrieval results and phase
62 transition processes based on the nature of the campaign and instrumentation. These studies have
63 various performances depending on their retrieval methods and assumptions during retrievals. Xi et al.
64 (2022) used the W-Band radar measurements and microwave radiometer retrieved cloud liquid water
65 path (LWP) to estimate cloud phase and macrophysical properties over the SO (North of 60° and South
66 of 60° latitude) for clouds sampled during the ship-based the Measurements of Aerosols, Radiation, and
67 Clouds over the Southern Ocean (MARCUS, Xi et al., 2022; Marcovecchio et al., 2023; McFarquhar
68 et al., 2016, 2021) campaign and estimated a greater frequency of mixed-phase clouds followed by ice
69 and liquid clouds. Ship-based measurements during the MARCUS can provide accurate cloud
70 boundaries and their vertical distributions. Wang & Sassen (2001) presented algorithms for retrieving
71 cloud macrophysical properties, such as boundary, thickness, phase, type, and precipitation, using a
72 combination of ground-based lidar, millimeter-wave radar, IR radiometer, and MWR measurements at
73 the ARM SGP CART site in Northern Oklahoma. Further, Shupe (2007) provided an array of ground-
74 based Lidar-Radar threshold values to estimate cloud hydrometeor phase including aerosols, liquid,
75 mix, ice, drizzle and rain designed for the study of Arctic clouds. Compared to the ground-based
76 measurements, the aircraft in situ measurements, however, can provide more reliable datasets without
77 the issues of retrieval methods and assumptions because aircraft can fly in greater proximity to the cloud
78 boundaries and even inside the cloud layers. Also, the onboard radar and lidar suffer less attenuation
79 than the ground-based remote sensors (Ewald et al., 2021).

80 The Southern Ocean Clouds, Radiation, Aerosol Transport Experimental Study (SOCRATES)
81 aircraft field campaign provided a valuable dataset to investigate the MBL clouds over the SO. The
82 SOCRATES was an aircraft-based campaign that used the National Science Foundation (NSF)/National
83 Center for Atmospheric Research (NCAR) Gulfstream-V (GV) research aircrafts based out of the coast
84 of Hobart, Tasmania (42-62°S and from 133°-163°W) from 15 January to 28 February 2018, targeting
85 cold sector boundary layer clouds and airborne sampling of in-, below- and above-cloud transects
86 obtaining both time series and vertical cloud information using an array of in-situ cloud and drizzle
87 sampling probes and radar-lidar instruments, mostly spanning a period of midnight to early morning
88 for each flight track on subsequent days. The in-situ probes and remote sensors (cloud lidar and radar)
89 onboard the aircraft flown during the SOCRATES campaign provide a direct observation of
90 precipitation, cloud particles, and aerosols below, inside and above the cloud layers sampled, along
91 with vertical profiles, for a better characterization of the MBL structure and free troposphere.
92 D'Alessandro (2021) used the suite of in-situ cloud and drizzle sampling probes (CDP & 2DS) onboard
93 the NCAR-GV aircraft during SOCRATES to estimate cloud phase heterogeneity and frequency
94 distributions predicting significant SLW and ice phase concentrations using a multinomial logistical
95 regression model (MLR). Romatschke and Vivekanandan. (2023) used a fuzzy logic scheme to classify
96 cloud hydrometeor type as a time-height profile using an array of cloud radar-lidar derived values.

97 According to Wang et al. (2012), integrating in-situ sampling capabilities with remote sensing
98 measurements offers significant advantages for studying atmospheric processes. In this context, the
99 integrated 2-dimensional cloud profiles obtained through remote sensing of microphysical processes



100 complement the detailed size-resolved distributions captured by in-situ cloud measurements. Therefore,
101 solely relying on either in-situ or remote sensing measurements can lead to certain disagreements in
102 cloud profile as the sampling probes can only detect cloud particles at the flying altitude while the
103 remote sensing profiles can provide vertically resolved cloud profile but with an offset of around 100-
104 200 meters. The lidars have a smaller operating wavelength compared to radar and provides well-
105 resolved vertical profiles for detecting aerosols, optically thin clouds and cloud boundaries, (Wang et
106 al., 2012, 2009; McGill et al., 2002) but its signals are easily attenuated by optically thick clouds, such
107 as liquid clouds (Sassen., 1991) as observed over the SO. Therefore, we exclusively used radar
108 measurements to estimate cloud boundaries and cloud phase for optically thick clouds in this study.
109 Furthermore, we also tune the High Spectral Resolution Lidar (HSRL) measured Particle
110 Depolarization Ratio (PLDR) thresholds based on the phase estimation method presented in this study.
111 This adjustment was seen necessary because the existing PLDR thresholds presented in Sassen (1991),
112 Intrieri (2002), and Shupe (2007) were developed for Arctic clouds, which differ significantly from the
113 low-level clouds over the Southern Ocean (SO).

114 In this study, we aim to use a combination of both in-situ and radar-based measurements during
115 SOCRATES to develop a new method to classify the MBL cloud phase and determine cloud boundaries
116 over the SO for low-level clouds. The newly developed classification method can be used to help answer
117 the following scientific questions:

- 118 1. What are the dominant cloud types, their associated cloud phase, base and top heights, and their
119 vertical distribution?
- 120 2. What are the phase-specific microphysical properties for SO low-level clouds sampled during
121 the SOCRATES campaign?

122 The paper is organized in the following manner: data and methods are introduced in Section 2. The
123 statistical results for all cloud properties during the SOCRATES campaign are presented in Section 3.
124 Cloud phase-specific results and comparisons with other algorithms for the low-level clouds are
125 discussed in Section 4, and finally, Conclusions and Summary are given in Section 5.

126 **2 Data and methods**

127 **2.1 SOCRATES aircraft campaign**

128 The Southern Ocean Clouds, Radiation, Aerosol Transport Experimental Study (SOCRATES) aircraft
129 field campaign was conducted over the SO with a total of 15 research flights from 15 January to 28
130 February 2018 (McFarquhar et al., 2021). During SOCRATES field campaign, the Cloud Droplet Probe
131 (CDP) and 2-dimensional stereo- particle imaging probe (2DS) were utilized to measure cloud and
132 drizzle microphysical properties, respectively. Additionally, HCR and HSRL were installed on the RV
133 aircraft to detect cloud structure, phase and boundaries (McFarquhar et al., 2021). HSRL particle linear
134 depolarization ratios (PLDR) were widely used as a screening tool for cloud phase determination with
135 liquid clouds having PLDR less than 0.11, mixed-phase clouds falling between 0.11 and 0.15, and ice
136 clouds having PLDRs greater than 0.15 (Shupe et al., 2005; Xi et al., 2022). The 2DS in-situ
137 measurements serve as an additional screening to eliminate the ice particles ($D > 200 \mu\text{m}$). More
138 instrumental details about the SOCRATES campaign can be found in McFarquhar et al. (2021).

139 The suite of in-situ probes and radar-lidar instruments onboard the SOCRATES aircraft is listed in
140 Table 1, along with their detection limits and uncertainties. The particle size distribution and number
141 concentration were retrieved from the CDP and 2DS microphysical probe measurements and merged



142 to create one continuous dataset with size bins from 2 to 40 μm corresponding to cloud droplets and 40
 143 μm above for drizzle particles (to 1280 μm), at a 1 Hz temporal resolution for each research-flight.
 144 Reflectivity (dBZ), Doppler Velocity (V_d) (m/s), and Spectrum Width (WID) (m/s) were retrieved from
 145 the original 2 Hz temporal resolution of the HCR radar measurements and were averaged to match the
 146 1 Hz frequency resolution of the in-situ probes and further interpolated to fixed radar-heights at a range
 147 gate of 19.2 meters. The same treatment was done for the HSRL-retrieved Backscatter Coefficient β
 148 ($\text{m}^{-1}\text{sr}^{-1}$) and Particle Linear Depolarization Ratio (PLDR) (unitless). The HSRL (lidar) signal is highly
 149 sensitive to greater cloud droplet concentrations and can be attenuated within a few hundred meters in
 150 liquid cloud layers (Ewald et al., 2021; Sassen, 1991). Thus, it is not used for phase or boundary
 151 estimation in optically thicker MBL clouds discussed in this paper. The atmospheric temperature ($^{\circ}\text{C}$)
 152 for the cloud samples was retrieved from the 2-dimensional ERA5 reanalysis product, which is available
 153 in the HCR-HSRL merged dataset at the EOL data archive. This dataset matches the vertical and
 154 temporal resolution of the HCR-HSRL data (NCAR/EOL HCR Team., 2023). Temperatures below -40
 155 $^{\circ}\text{C}$ are not considered during further analysis as they represent homogenous freezing temperatures
 156 (majorly all ice) and most mixed phases exist only over the range of -40 to 0°C (e.g., Shupe et al.,
 157 2007). The dataset is further filtered to keep only the nadir or zenith pointing direction of the HCR-
 158 HSRL merged dataset, all the in-transition or rotational pointing directions (which were not equal to
 159 ± 90 degrees) were removed. The 2DS particle morphology or habit imagery data (Wu and McFarquhar.,
 160 2019) was also retrieved and visualized using the Illinois/ Oklahoma Optical Probe Processing Software
 161 (XPMS2D, UIOOPS, McFarquhar et al., 2018).

162 **Table 1. Measurements from specific instruments used in this study and their relevant properties.**

	INSTRUMENT	MEASUREMENT	Size Range/Resolution	Uncertainties	REFERENCES
In-Situ Probes for Bulk Cloud Sampling	Cloud Droplet Probe (CDP)	Size distribution and concentration of hydrometeors with a diameter between 2-50 μm	2-50 μm	Cannot resolve non-spherical particles accurately	Lance et al., 2010
	Two-Dimensional, Stereo, Particle Imaging Probe (2D-S)	Size distribution and concentration of hydrometeors with a diameter between 10 to 1280 μm range	10- μm D>40 μm for all particles D> 200 μm for ice	Cannot resolve for particle sizes D <50 μm , also ice particle detection is certain only for D>200 μm .	Lawson et al., 2006; 2008 Baker et al., 2009 Wu and McFarquhar., 2019
Radar-Lidar remote sensors	HIAPER Cloud Radar (HCR)	Reflectivity, Doppler Velocity, Spectral Width, Linear Depolarization Ratio (LDR), etc.	~ 19 m in vertical resolution Frequency: 94.40 GHz	Attenuates for larger particle sizes	NCAR/EOL HCR Team., 2014 Romatschke et al., 2021 Vivekanandan et al., 2015
	High Spectral Resolution Lidar (HSRL)	Backscatter Coefficient, Particle Linear Depolarization Ratio (PLDR), Extinction Coefficient, etc.	Wavelength: 532 nm	Sensitive to optically thin cloud layers	NCAR/EOL HSRL Team., 2012 Eloranta., 2005

163

164

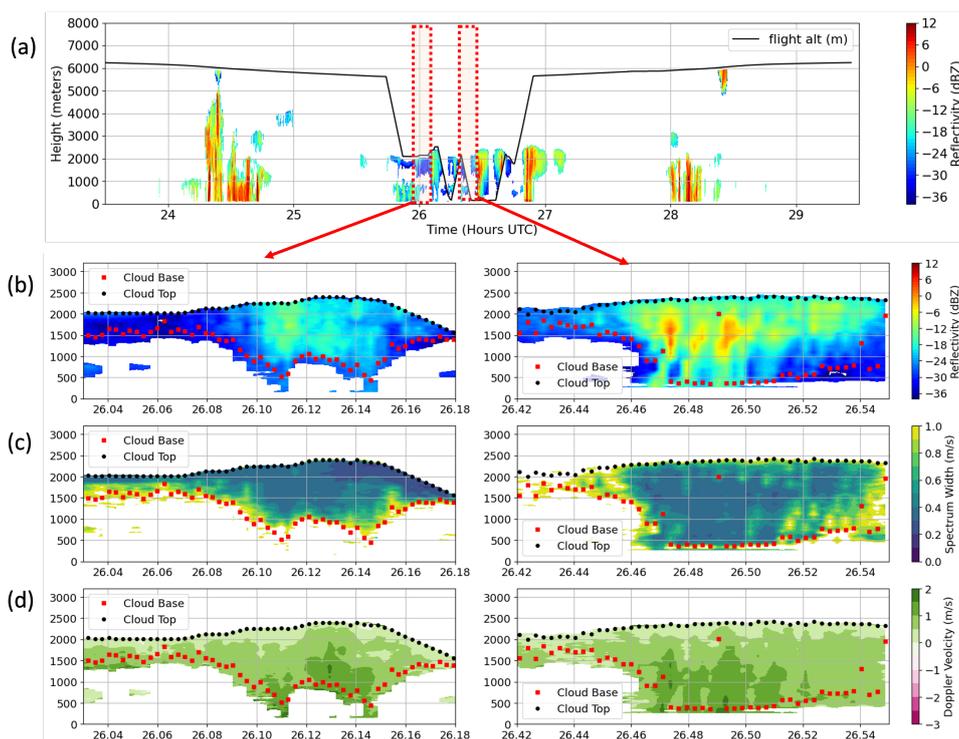


165 2.2 Estimation of cloud boundaries

166 There are multiple existing methods of estimating cloud base and top heights, for example, using
167 thresholds for lidar returned power, depolarization, or backscatter (e.g., Intrieri et al., 2002; Kang et al.,
168 2021, 2024) or thresholding in-situ measured vertically resolved liquid water path (LWP) or liquid
169 water content (LWC) and cloud droplet number concentration. For this study, the cloud base was
170 estimated as the lowest height (from the sea surface) where the HCR Spectrum Width (WID) Gradient
171 is the lowest in value (or highest negative gradient). The lowest WID gradient indicates the change from
172 a precipitation layer to the cloud layer where the gradient of spectrum width decreases sharply. The
173 cloud-base height (H_{base}) was also estimated using the HSRL backscatter coefficient threshold, but this
174 cloud-base height was found to be around 400 m higher than that derived from HCR spectrum width
175 gradient. Higher spectrum width around the cloud base indicates a greater turbulence and wider range
176 of particle velocities observed which correlate to potentially stronger turbulence, and likely drizzle or
177 precipitation. This argument is further improved by the aircraft in situ measured microphysical
178 properties.

179 The cloud-top height (H_{top}) is measured as the highest height (from the cloud base) where prominent
180 HCR reflectivity ($\text{dBZ} > -50$) is observed following the method of Kang et al. (2024). Finally, cloud
181 thickness (ΔH) is estimated as the difference between cloud-top and -base heights, $\Delta H = H_{\text{top}} - H_{\text{base}}$.
182 For double-layered clouds, each single-layer cloud-base and -top heights were identified separately but
183 are not reported in this study as only single-layered cloud types were used for further analysis. The
184 accuracy of the estimated cloud-top and -base heights for the low clouds have been verified by mapping
185 them on the radar detected cloud profile (Fig. 1.) and will be discussed in following sections. This
186 method of estimating H_{top} and H_{base} can be used to find cloud boundaries in the absence of a readily
187 available radiosonde or dropsonde measured cloud heights dataset.

188 A case study for the retrieved cloud boundaries using the HCR reflectivity and spectrum width
189 gradient is illustrated in Fig. 1(a-d). Using the spectrum width gradient for estimating cloud-base
190 heights allows finding cloud and drizzle base above the precipitating layer with minimal errors
191 compared to lidar HSRL-Backscatter values which attenuate faster for thicker cloud layers. Boundary
192 estimation was carried out for each sublayer separately for double-layered clouds (not shown). Isolated
193 cloud transects less than 50 meters in vertical height and 10 seconds in temporal width (which appear
194 as small, isolated dots or patches of reflectivity or spectrum width profiles in the following plot) are
195 ignored as noise.



196

197 **Figure 1. (a) HCR Reflectivity (dBZ) profile for the entire flight track for RF01 from 23:30 UTC**
 198 **(15 Jan 2018) to 05:30 UTC (16 Jan 2018). The solid black line in (a) indicates the flight altitude**
 199 **in meters. The two red boxes in (a) are the subsection for which the cloud-top and -base heights**
 200 **are displayed (b), (c), and (d). The left panels represent the cloud profiles when the flight was**
 201 **flying above the cloud top and radar pointed nadir, while the right panel shows a zenith-pointing**
 202 **radar cross-section with the flight flying below the cloud base. (b), (c), and (d) are the profiles of**
 203 **HCR reflectivity, spectrum width (WID) and Doppler Velocity (V_d) with the cloud tops (black**
 204 **squares) and cloud bases (red squares).**

205 **Table 2. Cloud classification using Base and Top heights.**

CLOUD TYPE	CLASSIFICATION METHOD
LOW (low-level clouds)	$H_{\text{top}} \leq 3\text{km}$, in a single layer
MID (middle level)	$H_{\text{base}} > 3\text{km}$ and $H_{\text{top}} \leq 6\text{km}$, in a single layer
HGH (high clouds)	$H_{\text{base}} > 6\text{km}$, in a single layer
MOL (mid-over-low)	$H_{\text{base}} < 3\text{km}$ and $H_{\text{top}} \leq 6\text{km}$, may not be single layer
HOM (high-over-middle)	$3\text{km} < H_{\text{base}} < 6\text{km}$, and $H_{\text{top}} > 6\text{km}$, may not be single layer
HML (high-over mid and low)	$H_{\text{base}} < 3\text{km}$, and $H_{\text{top}} \geq 6\text{km}$, extend over the whole tropospheric layer



206 2.3 Classification of Cloud type

207 After estimating the cloud-base, -top heights, and cloud thickness (H_{base} , H_{top} , ΔH), the cloud types are
208 categorized following a classification method described by Xi et al., 2010, and summarized in Table 2.
209 A single layer means that there is no other cloud layer above or below the classified cloud layer for the
210 time series.

211 Based on this classification method, a significant number of LOW ($H_{\text{top}} \leq 3\text{km}$) clouds were
212 identified followed by MOL ($H_{\text{base}} < 3\text{km}$, $H_{\text{top}} \leq 6\text{km}$) and MID ($H_{\text{base}} > 3\text{km}$, $H_{\text{top}} \leq 6\text{km}$). Some HGH
213 ($H_{\text{base}} > 6\text{km}$), HOM ($3\text{km} < H_{\text{base}} < 6\text{km}$, and $H_{\text{top}} > 6\text{km}$), and HML ($H_{\text{base}} < 3\text{km}$, and $H_{\text{top}} \geq 6\text{km}$) cloud
214 types were also identified but almost insignificant or negligible in number relative to LOW, MID, and
215 MOL types. Only a couple of flights had single or double-layered clouds with H_{base} and/or $H_{\text{top}} > 6\text{km}$,
216 which were ignored to optimize for statistical deviation and minimize errors. Notice that these results
217 are due to the selected cloud cases during the flight, which may not represent all the true cloud types.

218 Cloud phase estimation was only carried out for the single-layered LOW cloud type, which was the
219 predominant cloud type during the SOCRATES field campaign. The statistical results for the
220 predominant cloud types of LOW, MID and MOL are further discussed in Section 3.

221 2.4 In-Cloud Conditions

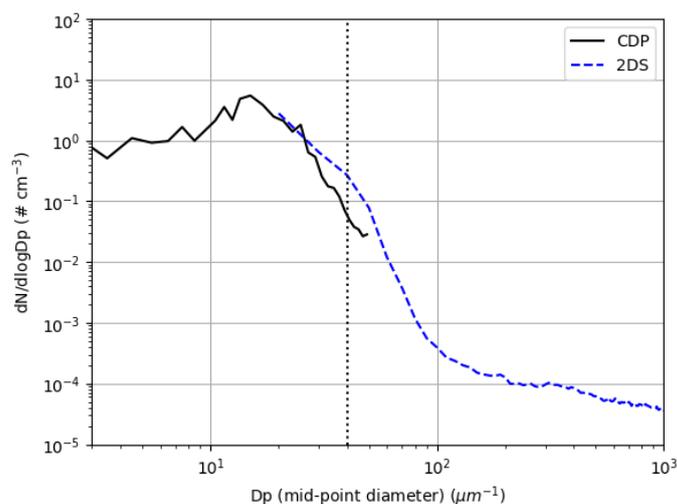
222 The cloud-droplet number concentration and particle size from the merged CDP+2DS dataset is used
223 to calculate a continuous liquid water content (LWC) in g/m^3 for cloud and drizzle particles, using the
224 equation (Kang et al., 2021; Zheng et al., 2024) as follows:

$$225 \quad \text{LWC} = \frac{4}{3} \pi \rho_w \sum_{i=1}^{\{n\}} r_i^3 \cdot N_i, \quad (1)$$

226 where ρ_w is the density of liquid water, r_i is the particle radius measured as droplet size distribution
227 from the CDP+2DS particle size bins, and N_i is the number concentration ($\#/\text{cm}^3$) per bin. The LWC
228 values are further used to compute the liquid water path (LWP) in g/m^2 as a function of cloud thickness
229 (ΔH) (Oh et al., 2018), as follows:

$$230 \quad \text{LWP} = \sum_{j=1}^{\{n\}} \text{LWC}_j \cdot \Delta H_j. \quad (2)$$

231 The in-cloud conditions were constrained to keep cloud samples only containing LWC greater than
232 $0.001 \text{ g}/\text{m}^3$, to remove noise or uncertainty in measurements. CDP number concentration less than 1
233 cm^{-3} corresponds to ice phase observations in particles with size less than $50 \mu\text{m}$, and greater than or
234 equal to 1 cm^{-3} corresponds to the liquid phase (D'Alessandro et al., 2021). Hence, choosing LWC
235 threshold is based on the decision to ensure a significant cloud density and cloud number concentration,
236 and remove clear-sky conditions or noise from aerosols. The number concentration of ice particles with
237 diameters greater than $200 \mu\text{m}$ is very low (Zheng et al., 2024), as shown in Fig. 2, indicating that most
238 ice phase particles occur below the 2DS-defined threshold of $200 \mu\text{m}$ for ice particle size distribution
239 (Wu and McFarquhar, 2019).



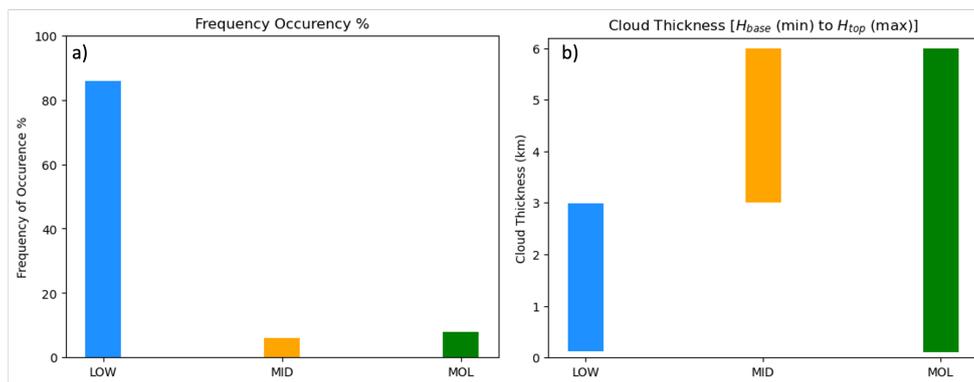
240

241 **Figure 2. Cloud and Drizzle (CDP+2DS) size distributions aggregated for the 15 research flights**
242 **during SOCRATES. The dashed line at $D_p = 40 \mu\text{m}$ denotes the separation from cloud to drizzle**
243 **droplets.**

244 There is a small offset in the calculated LWP because LWC is derived from in-situ cloud (CDP)
245 microphysical properties while cloud thickness is derived from the HCR and HSRL measurements.
246 However, the difference was insignificant when these results were compared to the average LWP values
247 observed over the SO by previous studies like Xi et al. (2022) and Mace et al. (2021). Future work
248 could be done on finding the LWC and LWP as a function of the cloud vertical height profiles matched
249 to the HCR-HSRL profiles, following the methods mentioned in Vivekanandan et al. (2020). Ice water
250 content (IWC) in g/m^3 was also retrieved from the 2DS dataset for particle sizes $\geq 200 \mu\text{m}$. The 2-
251 dimensional HCR-HSRL parameters were further constrained for the cloud base and top heights for the
252 classified cloud types in the vertical dimension and for the LWC threshold in the time dimension. The
253 2-dimensional air temperature ($^{\circ}\text{C}$) from ERA5 was filtered to extract the cloud-base and -top
254 temperatures. The aircraft-measured air temperature is not used in this study as it only measures
255 temperature at the fixed flying altitude of the aircraft.

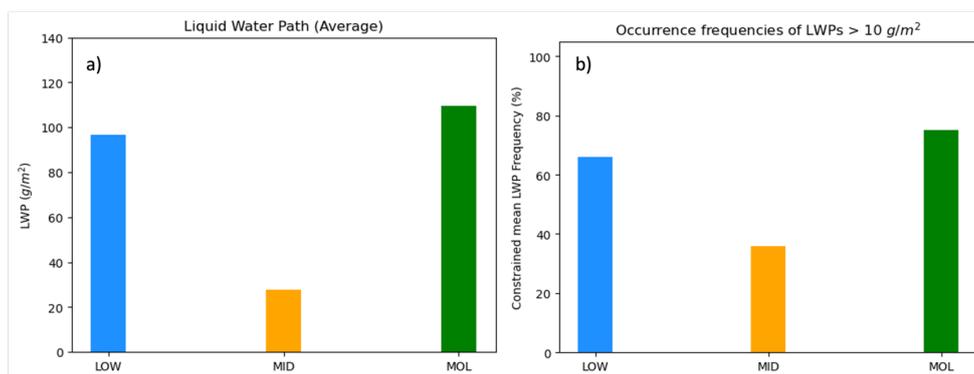
256 3 Statistical results for prominent cloud types

257 The most prominent cloud types identified using the cloud boundary estimation discussed in the Section
258 2.3, such as LOW, MID, and MOL, which are consistent of $\sim 85\text{-}90\%$ occurring frequencies in total
259 from the 15 research flights during SOCRATES. Figure 3 summarizes the occurrence frequencies of
260 the classified single-layered LOW, MID, and MOL clouds along with their vertical structures or the
261 thickness (in km). Multilayered clouds were not considered for this classification due to their negligible
262 occurrence frequencies compared to the single-layered clouds. LOW clouds are the most observed
263 cloud type ($\sim 90\%$) compared to the other two cloud types (less than 10%), due to the nature of sampling
264 and targeted cloud sector of the SOCRATES campaign. Most of the research flights flew below 6-7 km
265 over the SO studying MBL clouds with greater amount of SLW (Schima et al., 2022).



266
267 **Figure 3. (a) The occurrence frequencies of single-layered LOW, MID, and MOL clouds, b) the**
268 **average thickness for each cloud type.**

269 Figure 4 visualizes the LWP frequencies for each cloud type averaged from the 15 research flights
270 along with the constrained LWP frequency which shows the percentage occurrence of LWP above the
271 threshold of 10 g/m^2 for each cloud type. Amongst the 15 flights, the maximum average LWP is
272 observed for MOL clouds at around 370 g/m^2 followed by LOW at 208 g/m^2 and very low for MID
273 clouds at around 65.8 g/m^2 . The overall statistical results for the LOW, MID, and MOL classified
274 cloud types are summarized in Table 3.



275
276 **Figure 4. a) Averaged LWP for each cloud type from the 15 research flights. b) Constrained LWP**
277 **occurrence frequencies for LWPs greater than 10 g/m^2 which is the threshold for classifying liquid**
278 **and mix phase from ice-phase cloud transects. Percentages for $\text{LWP} > 10 \text{ g/m}^2$ are approximately**
279 **66%, 36% and 75% for LOW, MID and MOL clouds, respectively.**

280

281

282

283

284



285 **Table 3. Mean, standard deviation, minimum and maximum ranges for the estimated cloud base**
286 **and top heights along with the calculated LWP values for each single-layered cloud type.**

	LOW	MID	MOL
H_{base} ± SD	1.01 ± 0.6	4.16 ± 0.80	1.56 ± 0.93
Min, Max (km)	0.13, 2.97	3.01, 5.97	0.11, 2.99
H_{top} ± SD	1.57 ± 0.58	4.79 ± 0.84	4.18 ± 1.04
Min, Max (km)	0.15, 2.99	3.03, 5.99	3.01, 5.99
LWP (mean) ± SD	96.7 ± 187	27.9±73	109.48 ± 208
Max (g/m²)	2732	963	2121

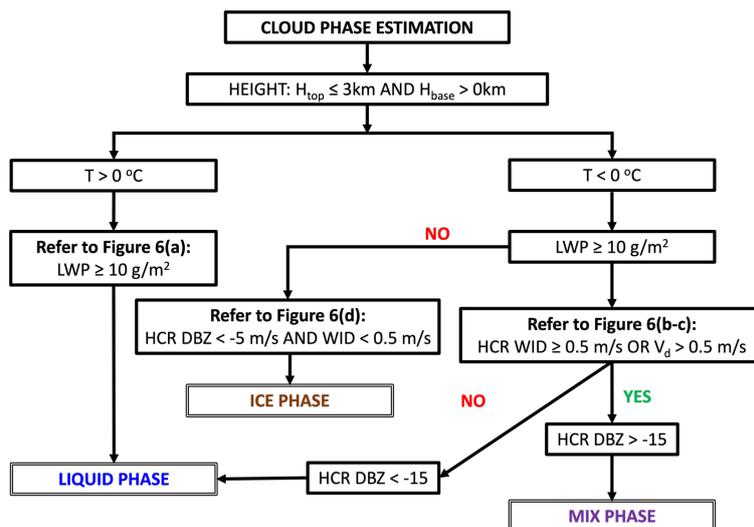
287 4 Low cloud phase retrieval results and discussions

288 As shown in Figure 3, LOW clouds are dominant cloud type (~90%) observed during SOCRATES. In
289 this section, we discuss how to determine LOW cloud phase. The estimated cloud base and top heights,
290 along with other radar-lidar and in-situ variables, were aggregated using the median to a temporal
291 resolution of 10 seconds (0.1 Hz). This aggregation was constrained to the cloud boundaries and single-
292 layered low-level cloud types to ensure a more continuous data distribution and to minimize outliers,
293 thereby improving statistical consistency before phase determination.

294

295 4.1 Determination of Cloud Phase

296 Figure 5 describes the flow-chart of determining cloud phase for the classified low-level clouds (LOW)
297 with cloud-top heights below 3 km after constraining for the in-cloud conditions ($LWC > 0.001 \text{ g/m}^3$).
298 The phase partitioning method described in this section is used simultaneously as combined filters to
299 classify the cloud phase as a 2-dimensional phase profile of liquid, mix and ice phase. LWP threshold
300 was estimated after constructing probability density function (PDF) plots for the classified LOW, MID,
301 MOL, HGH, and HOM clouds which returned a peak of less than 10 g/m^2 in LWP values for the HGH
302 and HOM clouds which are prevalently ice-dominated clouds. There are significant overlaps between
303 the LWP PDFs for classified cloud types, which results in some inconsistencies and uncertainties. For
304 example, LOW clouds also display a peak in LWP values less than 10 g/m^2 but simultaneously also
305 show consistently greater frequency for LWP values even greater than 200 g/m^2 . Whereas the LWP
306 frequencies for other cloud types diminish to zero after 15 or 20 g/m^2 . The LWP value of $\sim 10 \text{ g/m}^2$ also
307 lies around the uncertainty value for LWP measurement over SO (Kang et al., 2021). While LWP values
308 for LOW, MID and MOL cloud types are significantly higher, most of the LWPs for HGH and HOM
309 clouds are below 10 g/m^2 . Therefore, we use $LWP = 10 \text{ g/m}^2$ as a threshold to determine cloud phases
310 where cloud samples with $LWP < 10 \text{ g/m}^2$ is classified as ice clouds, while $LWP \geq 10 \text{ g/m}^2$ as mixed-
311 phase or liquid clouds.



312
 313
 314
 315
 316
 317

Figure 5. Flow chart depicting the phase classification of single-layered LOW clouds during SOCRATES. Spectrum Width (WID), Doppler Velocities (V_d) and reflectivity (dBZ) are measured by HCR radar, and Liquid Water Path (LWP) is calculated from in-situ measurements. Temperature is provided from ERA5 reanalysis air temperature matched to the HCR-HSRL merged dataset.

318
 319
 320
 321
 322
 323
 324
 325
 326
 327
 328
 329
 330
 331
 332
 333
 334
 335
 336
 337
 338
 339
 340
 341
 342

In addition to the LWP threshold, the profile of atmospheric temperature provides another threshold for determining LOW cloud phase. where temperature is greater than $0\text{ }^{\circ}\text{C}$ is classified as liquid while for temperature between -40 to $0\text{ }^{\circ}\text{C}$ is further analyzed for categorizing between liquid, mixed and ice. As shown in Fig. 5, if LWPs are equal or greater than 10 g/m^2 and T is higher than $0\text{ }^{\circ}\text{C}$, then the cloud samples are classified as liquid clouds. For ice clouds, it is as simple as classifying liquid clouds where the cloud samples are defined ice clouds when both $LWP < 10\text{ g/m}^2$ and $T < 0\text{ }^{\circ}\text{C}$, whereas it becomes more complicated for mixed-phase clouds. For the cloud samples with $T > 0\text{ }^{\circ}\text{C}$ and reflectivity < -15 dBZ are considered as liquid cloud droplets because most of drizzle drops have higher reflectivity (> -15 dBZ, Wu et al., 2020). Low WIDs correspond to homogenous single-phase of cloud hydrometeors while a broad range of WIDs suggest multiple phases and/or significant turbulence and wind shear (Shupe., 2007). The regions with both low WID and $V_d (< 0.5\text{ m/s}$, weak turbulence) are classified as liquid phase with dominant small liquid cloud droplets and SLW. The cloud samples are classified as mixed-phase clouds when both Doppler spectrum width (WID) and Doppler velocity (V_d) values are greater than 0.5 m/s (downdraft) which represent a greater variability of velocity, greater turbulence in cloud droplets and variable size distribution including large ice or drizzle-sized particles. The cloud samples with either $WID > 0.5\text{ m/s}$ and $V_d < 0.5\text{ m/s}$ (or $WID < 0.5\text{ m/s}$ and $V_d > 0.5\text{ m/s}$) i.e. regions of high WID but low V_d (updrafts) or low WID and high V_d (downdrafts) are re-classified into mixed phase if the reflectivity (dBZ) > -15 and liquid phase if the reflectivity (dBZ) < -15 . Radar reflectivity is a function of the sixth moment of the particle size (Wang et al., 2009) hence small and uniform liquid cloud droplets exhibit significantly lower reflectivity while mixed-phase clouds normally exhibit higher reflectivity values with a higher in-homogenous particle size distribution and greater density variability. Furthermore, the cloud samples with reflectivity > 5 dBZ represent precipitation (rain or snow depending on the temperature) and hence these samples are omitted in this study. Furthermore, the cloud samples with reflectivity > 5 dBZ represent precipitation (rain or snow depending on the temperature) and hence these samples are omitted in this study.

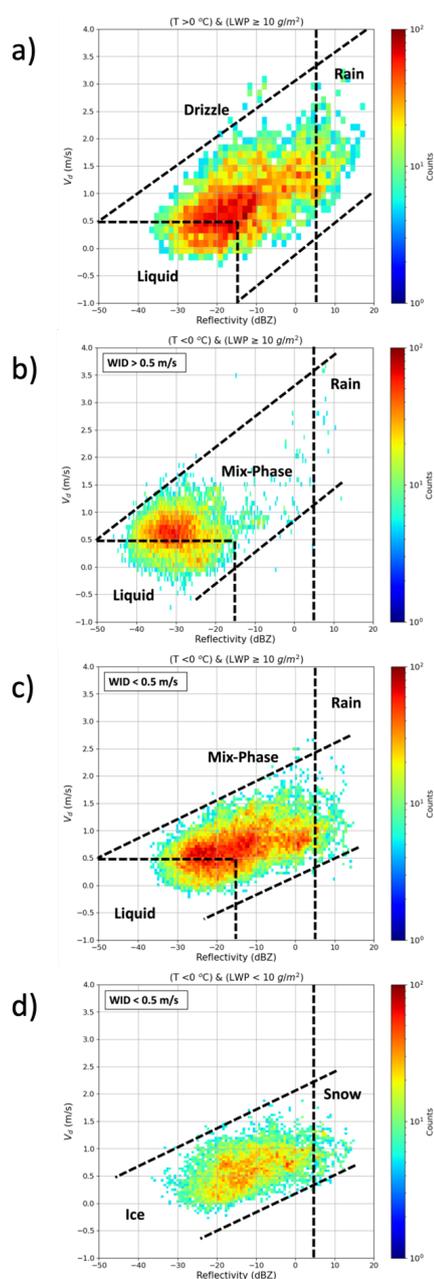


343 The estimation of WID, V_d , and dBZ thresholds was determined by the average values observed for
344 each cloud layer based on the tropospheric height and at the estimated cloud base. These values were
345 aggregated by prioritizing regions with more measurements over those with less ones, along with
346 considering the cloud density at each layer, further comparing with existing studies, such as Xi et al.
347 (2022) and Shupe (2007). Although these constraints were specifically tuned for clouds sampled during
348 the SOCRATES campaign, we expect them to be broadly applicable to MBL clouds over the Southern
349 Ocean.

350 To further demonstrate our phase classification methodology using T, LWP, WID, V_d , and the
351 reflectivity (dBZ) as shown in Fig. 5, we present the bivariate histograms of liquid, mixed-phase and
352 ice clouds in Fig. 6. Figure 6a illustrates the liquid cloud droplets, drizzle and rain drops based on radar
353 reflectivity (-15 dBZ and 5 dBZ) and Doppler velocity ($V_d < 0.5$ m/s) at higher temperatures ($T > 0$ °C).
354 As shown in Fig. 6a, drizzle drops are dominant in the liquid clouds at $T > 0$ °C, with higher radar
355 reflectivity and Doppler velocity. Marcovecchio et al., 2024 found that there is a higher drizzle
356 frequency rate (71.8%) over SO using the ship-based radar-lidar measurements during the Measurement
357 of Aerosols, Radiation, and CloUds over the Southern Ocean (MARCUS) field campaign than the
358 ground-based radar-lidar measurements at the ARM East North Atlantic (ENA) site (45.1%). Figures
359 6b-6c present the classification of mixed-phase and liquid clouds where $WID \geq 0.5$ or < 0.5 m/s, with
360 $T < 0$ °C and $LWP \geq 10$ g/m², using V_d and dBZ thresholds, where higher dBZ (> -15) corresponds to
361 mixed while lower dBZ (< -15) and lower V_d (< 0.5 m/s) corresponds to liquid phase. Liquid droplets
362 due to their smaller size and uniform homogenous distribution exhibit lower dBZ, and lower V_d
363 (updraft). Higher WID in liquid droplets mostly represent regions of turbulence and wind shear. The
364 2D pattern in Fig. 6c mimics that of Figure 6a, indicating that liquid clouds with more drizzle and
365 mixed-phase clouds are dominant for LOW clouds over SO. There is a linear relationship between cloud
366 reflectivity (dBZ) and Doppler velocity (V_d) for ice clouds, similar to liquid and mixed-phase clouds,
367 except for Fig. 6b. Figure 6(d) represents regions classified as ice based on lower temperatures ($T < 0$
368 °C) and $LWP < 10$ g/m². The results of Figs. 6c and 6d suggest that the ice particle size distributions
369 are not as broader as expected even though their particle sizes are much larger with higher radar
370 reflectivity and Doppler velocity. The threshold of very high reflectivity, dBZ > 5 represents regions of
371 precipitation (rain or snow) and is not considered in the final phase classification.

372 The phase classification methodology illustrated in Figs. 5 and 6(a-d) are used together
373 simultaneously for estimating the liquid, mixed and ice phases for the low-level clouds in this study.
374 The described method using radar-retrieved and in-situ measurements in this study was compared with
375 the similar thresholding values defined in previous studies (Xi et al., 2022; Romatschke &
376 Vivekanandan., 2023; Desai et al., 2023; Wu et al., 2020; Shupe., 2007) for coherence and consistency
377 in the phase retrieval methodology. There could be some cases where the specified V_d and the WID
378 threshold yield in a mix or liquid-phase conditions even if the true dominant phase is ice at that level
379 (Shupe, 2007).

380 A 2-dimensional cloud phase is determined as a time-height dimensional profile for the valid cloud
381 segments based on the discussed phase estimation method. Furthermore, the 2D phase profile is used
382 to find a 1-dimensional dominant phase profile along the time dimension, where the dominant phase is
383 determined by finding the sample that has the highest sample count along any vertical transect. For
384 example, if at any time interval the sample count of a particular phase (say Liquid) is greater than the
385 sample count of the other two phases (Ice and Mix) along the vertical transect, then liquid is the
386 dominant phase at that time interval, i.e. the phase with the majority sample count at a vertical column
387 is the dominant phase at that instance. Furthermore, if the sample count of ice is equal to liquid along
388 any vertical transect, then the dominant phase at that time interval is mixed phase. This 1-dimensional
389 dominant phase with a temporal resolution of 10 seconds phase partitioning will be used to determine
390 the phase-specific cloud macrophysical results in the next section.



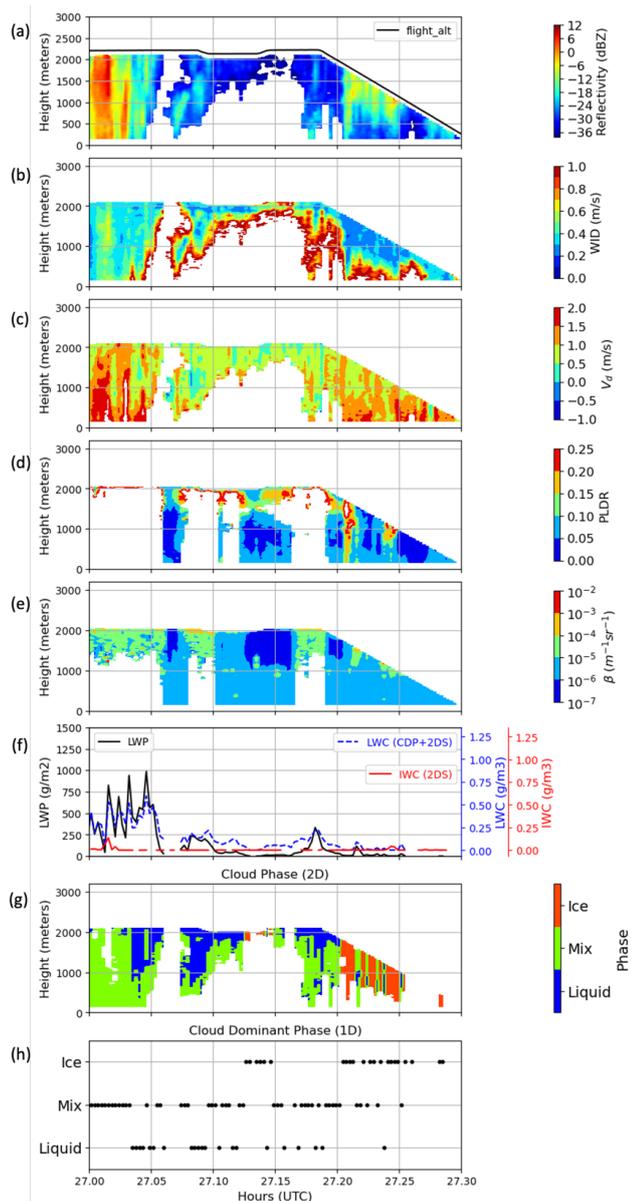
391
392 **Figure 6. (a-d) The bivariate histograms of radar reflectivity (dBZ) and Doppler velocity (V_d) for**
393 **different spectrum widths (WID), LWPs and Temperatures (T) to demonstrate the classified**
394 **liquid, ice and mixed phase cloud samples. The colorbar shows the sample count in each bin in a**
395 **logarithmic scale and the dashed lines represent the threshold values for the phase classification.**
396 **It is to be noted that the categories rain, drizzle, and snow are not taken into consideration in this**
397 **study.**



398 **4.2 Cloud Phase Determination Results**

399 The liquid-phase clouds are firstly determined where both temperature (T) is greater than $0\text{ }^{\circ}\text{C}$ and cloud
400 LWP is greater than 10 g/m^2 , while when T is lower than $0\text{ }^{\circ}\text{C}$ and cloud LWP is greater than 10 g/m^2 ,
401 the SLW clouds are determined when both WID and V_d are less than 0.5 m/s . Large ice particles are
402 much heavier than small liquid cloud droplets with a broader spectrum width and greater fall speeds
403 (Xi et al., 2022). The dependence on a linear LWP calculation as per the phase algorithm in this study
404 adds some difficulty in resolving the exact hydrometeor phase in a vertical column. For instance, there
405 could be cloud layers with an ice-phase top and liquid or mix-dominated base, but the LWP constraint
406 considers the whole column to be ice-phase if the $\text{LWP} < 10\text{ g/m}^2$. A significant number of mixed-
407 phase cloud samples were found at the cloud base due to broader WID and larger V_d values, which
408 could be attributed to the presence of either larger drizzle drops or ice particles.

409 These estimated phase retrievals are illustrated in Fig. 7(a-h) from one selected case, which was
410 chosen arbitrarily to offer visual clarity in phase profiles. The cloud phase presented in Fig. 7g is the 2-
411 dimensional phase retrieval method but may be not highly depictive of the actual cloud phase, whereas
412 Fig. 7h is the dominant cloud phase for each vertical transect retrieved from the 2D phase data where a
413 phase is considered dominant if its sample count is greater than the other two in the same vertical
414 column. This dominant cloud phase inferred from this 2D data along the vertical axis returns reasonably
415 accurate findings compared to other phase detection studies over the SO. Note that the cloud phase is
416 not available for very low LWC values due to the constraint used for in-cloud conditions.
417



418
419 **Figure 7.** A case study for flight RF09 during SOCRATES illustrating the phase-detection
420 algorithm in this study. (a) The HCR Reflectivity (dBZ) with the flight altitude in meters (black
421 line), (b) Spectrum Width (WID), and (c) Doppler Velocity (V_d) profiles. (d) and (e) represent the
422 HSRL (lidar) Particle Depolarization Ratio (PLDR) and Backscatter Coefficient (β). (f)
423 represents the LWP, LWC, IWC values for each determined phase in (d). (g) and (h) represent
424 the determined 2-D and dominant cloud phase. The time series is in decimal points where 27
425 hours is 3:00 UTC.



426 Higher IWC values correspond to ice phase particles greater than 200 μm in size. It is noticeable
427 that the ice phase also exists for very low or negligible IWC values which correlates to very small-sized
428 ice particles. The cloud transects where the dominant phase is liquid but also has a significant amount
429 of mixed phase around the cloud base is mostly indicative of drizzle or precipitation-size particles.

430 Inspecting the 2DS particle probe imagery (not shown in this paper) reveals that liquid cloud
431 droplets are mostly present in the form of spherical shape, and large ice particles have irregular shape,
432 while small ice particles cannot be resolved very well using the 2DS probes. The 2DS images
433 demonstrate that liquid cloud droplets are dominant at the upper levels of cloud layer, while a mixture
434 of liquid cloud droplets and ice particles exists at the lower levels. Large ice particles ($D_p > 50 \mu\text{m}$) are
435 easily identified by 2DS images, while it is challenging to distinguish small ice particles with cloud
436 droplets from 2DS imagery. D'Alessandro et al. (2021) developed a phase-determination method by
437 visually inspecting the 2DS particle imagery for particles of size greater than 50 μm and feeding this
438 training data to a multinomial logistic regression (MLR) model to classify them as liquid, mix or ice
439 phase. For the particles of size smaller than 50 μm , they were classified using a simple CDP number
440 concentration thresholding method: $N_c < 1 \text{ cm}^{-3}$ corresponds to ice phase and $N_c > 1 \text{ cm}^{-3}$ represents
441 liquid phase.

442 Table 4a lists the comparison of the phase determination using the MLR method (D'Alessandro et
443 al., 2022; 2021) and this study. With a total of 2335 overlapping samples, there are 45.7%, 26.2% and
444 28.0% of classified liquid, mixed-phase and ice clouds from this study, while they are 80.4%, 11.6%
445 and 7.9% from the MLR method. This comparison indicates that more liquid, but less mixed-phase and
446 ice cloud are identified by the MLR method than our results for the overlapping samples. Of the three
447 categories, there are a total of 995 samples of liquid clouds are identified by both the MLR method and
448 our study at the same timestamps, which accounts for 93.3% of classified liquid clouds from this study
449 and 53.0% of classified liquid clouds from the MLR method. The overlaps in ice and mixed-phase
450 clouds from these two methods are much less than their liquid cloud counterparts. The 162 (140)
451 overlapping samples for ice (mix) correspond to 87% (51%) of classified ice (mix) cloud samples from
452 MLR method and 24.7% (22.83%) of classified ice (mix) samples detected by this study. Note that
453 these percentages are just based on the matched dataset samples and do not represent the entire dataset
454 for both MLR, and the dominant cloud phase determined by this study.

455 To further evaluate the cloud phase partitioning method, we compare the classified phases from this
456 study with the MLR method and Shupe et al. (2005) and Intrieri et al. (2002) method for the classified
457 low-level cloud samples for the 15 research flights during SOCRATES. Shupe et al. (2005) and Intrieri
458 et al. (2002) used the lidar median PLDR (particle depolarization ratio) values to classify liquid (PLDR
459 < 0.11), mix ($0.11 < \text{PLDR} < 0.15$) and ice (PLDR > 0.15), respectively. As expected, the percentages
460 determined by this study in Table 4b are similar to the results in Table 4a, the percentage of liquid
461 clouds classified by this study is ~ 10 to 20% lower, but ~ 10 to 15% higher in mixed-phased clouds
462 compared to those classified from both the methods of MLR and Shupe et al. (2005). The ice clouds
463 classified from this study are $\sim 15\%$ higher than those detected by MLR but $\sim 10\%$ lower than those
464 classified using Shupe. (2005) and Intrieri. (2002) method. This comparison is very reasonable given
465 that our method is developed from aircraft in measurements and radar-measurements over SO, while
466 the method developed by Intrieri et al., 2002 and Shupe et al., 2005 were based on the ground-based
467 lidar measurements over Arctic regions and MLR uses a machine learning algorithm trained over the
468 in-situ cloud and drizzle droplet measurements (CDP+2DS). The other reason for the difference lies in
469 the in-cloud constraints ($\text{LWC} > 0.001 \text{ g/m}^3$ to define in-cloud samples) used in our method which were
470 not used for the other two methods. Furthermore, MLR also reported a significantly high number of
471 unclassified cloud samples ($\sim 56\%$) for aircraft-measured in-situ temperatures above freezing point
472 ($> 0^\circ\text{C}$) which were not included in this phase-percentage calculation for low clouds using MLR (Table
473 4(b) column 2).



474 If we treat the results classified in this study as a reference, the lidar median PLDR values to classify
475 liquid, mixed and ice clouds may need to be tuned slightly for SO low clouds. The existing PLDR
476 thresholds (<0.11 for liquid, $0.11-0.15$ for mixed, and >0.15 for ice phase clouds) as defined by Sassen
477 (1991), Intrieri (2002), and Shupe (2007), were originally established for Arctic clouds, which are
478 characteristically different from the MBL clouds over the Southern Ocean (SO). Using the classified
479 results in this study as a reference, we tune the existing HSRL PLDR thresholds for SO low-level clouds
480 and have the updated thresholds of PLDR < 0.09 for liquid phase, $0.09-0.18$ for mixed phase, and >0.18
481 for ice phase clouds. This adjustment was based on a simple analysis of the low cloud samples measured
482 simultaneously by both radar and lidar. Further scrutiny may be necessary to estimate the accuracy of
483 these thresholds for low-level clouds over SO, and this could be a focus for future research.

484 **Table (4a). Comparison of the phase determination between MLR method cloud phase product**
485 **(D'Alessandro et al., 2022) and this study matched at the same temporal resolution (10 secs).**
486 **Presented number are raw sample counts.**

MLR Method/ This Study	Ice (this study)	Mix Phase (this study)	Liquid (this study)
Ice (MLR)	162	16	8
Mixed Phase (MLR)	67	140	64
Liquid (MLR)	426	457	995

487
488 **Table (4b). The cloud phase partitioning for each phase-type determined using this method**
489 **(dominant phase) compared with the MLR method and Shupe (2005), Intrieri (2002) method for**
490 **the classified low cloud samples during SOCRATES. The data is aggregated to a 10 second sample**
491 **interval. The unclassified cloud samples in the MLR cloud phase product are not included in the**
492 **sample % calculation in column 2, and the in-cloud constraint ($LWC > 0.001 \text{ g/m}^3$) is not included**
493 **for phase detected by MLR (column 2) and Shupe (2005), Intrieri (2002) (column 3).**

	This Study	MLR Method	Shupe et al., 2005; Intrieri et al., 2002 Method
Liquid %	45.4	71.7	52.3
Mix %	22.2	10.3	5.5
Ice %	32.5	18.0	42.2

494 As previously mentioned, it's important to note that these three classification methods are different.
495 The MLR method determines cloud phase based on tuning a MLR (multinomial logistic regression)
496 model to cloud hydrometeors sampled using the in-situ probes (CDP+2DS) onboard the NCAR/GV
497 aircraft during SOCRATES, while we used both in-situ and radar measurements in this study. The
498 HSRL lidar method is purely dependent on the PLDR thresholds. The HSRL lidar detects a smaller
499 fraction of the cloud fraction compared to the HCR radar, as lidar is highly attenuated for thicker cloud
500 layers whereas HCR radar can offer a well-resolved cloud profile. Consequently, the radar and lidar do
501 not provide measurements for the exact same cloud layers, with an overlap region of only about 8%.
502 Therefore, while the comparison between these three methods is not entirely straightforward, it provides
503 a reasonable rough estimation for comparing the phase estimations across a linear time dimension.

504

505



506 **4.3 Cloud characteristics for each determined cloud phase**

507 Table 5 lists the summarized macrophysical cloud properties for each classified phase, based on the 1-
 508 dimensional dominant phase from all 15 research flights during SOCRATES. The statistical results
 509 listed in Table 5 include sample counts (and percentages) along with mean and standard deviation for
 510 cloud-base and -top temperatures (T_{base} and T_{top}) and heights (H_{base} and H_{top}), cloud thickness (ΔH) and
 511 LWP.

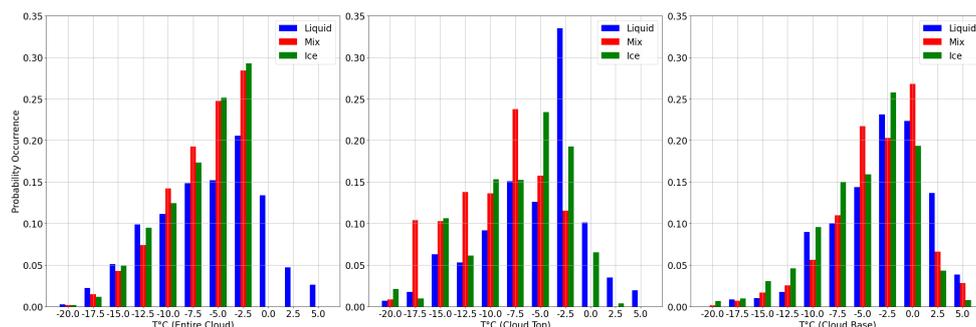
512
 513 **Table 5. Summaries of cloud macrophysical properties for each determined cloud phase**

Phase	Samples	T_{base} (°C)	T_{top} (°C)	H_{base} (km)	H_{top} (km)	ΔH (km)	LWP (g/m^2)
Ice	1043 (~32.5%)	-3.5±4.6	-6.0±4.8	1.12±0.63	1.59±0.61	0.47	2.7±2.6
Mixed-phase	712 (~22.2%)	-2.1±4.3	-8.2±4.8	0.74±0.53	1.65±0.60	0.91	200.5±267
Liquid	1458 (~45.4%)	-1.2±4.9	-3.9±5.4	0.90±0.54	1.34±0.59	0.44	89.7±100

514

515 **4.3.1 Cloud-base and -top temperatures (T_{base} and T_{top})**

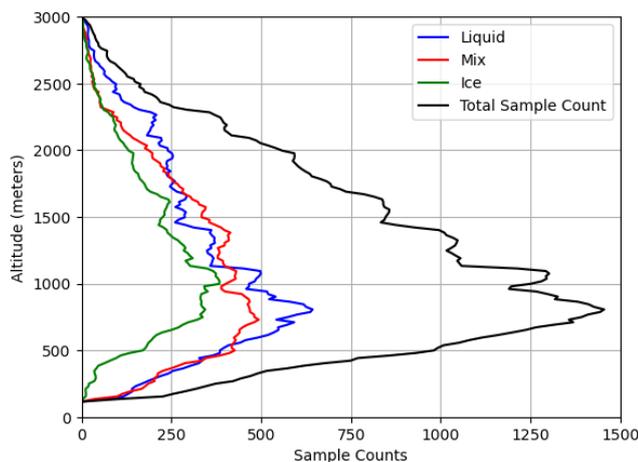
516 Low clouds generally exhibit higher temperature trends than the recorded aircraft temperature at the
 517 actual flying levels because of the difference in tropospheric altitude of the flight and the actual cloud
 518 boundaries. The ERA5 air temperature is used to extract the temperature at the cloud base and cloud
 519 height altitudes. Figure 8(a) shows the occurrence probabilities of the estimated cloud phases against
 520 the ERA5 air temperature for the entire cloud transect, highlighting that all the cloud phases have the
 521 highest occurrence in the range of -5 to -2.5 °C, while no ice and mixed phase exist at temperatures
 522 greater than 0 °C, 100% liquid-phase concentration is observed at $T > 0$ °C. The frequency distributions
 523 in Fig. 8 (b-c) show that all T_{top} samples from three phases increase monotonically from -20 °C, peak
 524 at -7.5 and -5 °C for mix and ice respectively, and -2.5 °C for liquid-phase, and quickly vanish after 0
 525 °C except for liquid samples. The frequency distributions of T_{base} samples from three phases almost
 526 mimic their T_{top} counterparts but with different peaks: The maximum frequency of liquid and ice phase
 527 occurs at -2.5 °C, while mixed-phase T_{base} remains at 0 °C. The different peaks in T_{base} samples from
 528 three phases have reflected in their mean H_{base} where the mean ice-phase H_{base} is 1.12 km, higher than
 529 other two H_{base} (0.74 and 0.90 km). T_{base} and T_{top} for liquid phase have the highest frequency at near -1
 530 °C. Ice and mixed-phase cloud temperatures show similar trends with most samples around lower
 531 temperatures. Interestingly the peaked T_{base} of mixed-phase clouds occurs at 0 °C because most of the
 532 mixed phase cloud samples occur around the cloud base where their temperatures are higher than cloud-
 533 top ones. It should also be noted that this analysis considers only the dominant phase for each layer
 534 (Fig. 8b-c), but the 2-dimensional phase is exclusively liquid for temperatures greater than 0 °C (Fig.
 535 8a) as discussed in the phase determination method.



536
537 **Figure 8. Probability distribution of the entire cloud layer temperature (T) from ERA5 air**
538 **temperature, cloud-top (T_{top}) and cloud-base (T_{base}) temperatures for each determined phase**

539 4.3.2 Profiles of determined cloud phase and radar observations

540 Figure 9 shows the vertical distributions of classified liquid, mixed-phase and ice cloud samples, as
541 well as the total samples of LOW clouds from 0 to 3 km (retrieved from the 2-dimensional cloud phase
542 profile). As mentioned above, liquid clouds are dominant, and its occurrence has the highest frequency
543 around 0.75 – 1.2 km. The ice cloud occurrence follows the trend of liquid clouds with the higher
544 frequencies at the levels of 0.75-1.5 km. Differing to liquid and ice clouds, the mixed-phase occurrence
545 is evenly distributed in the cloud layer with higher sample counts from 0.5 km to 1.5 km. It should be
546 noted that the sample counts of all three phases diminish to 0 at around 150 m which is where the
547 estimated cloud base lies for low clouds in this study.



548
549 **Figure 9. Profiles of the cloud samples for each determined cloud phase along with the total**
550 **sample number (black line).**

551 To further investigate the vertical distribution of classified liquid, mixed-phase, and ice clouds in
552 LOW clouds during SOCRATES, we plot the normalized vertical distributions of HCR reflectivity
553 (dBZ), Doppler Velocity (m/s) and Spectrum Width (m/s) in Fig. 10 (Contoured Frequency Altitude
554 Diagram, CFAD).

555 Figures 10a-10c show the CFADs of determined liquid cloud samples where most of radar
556 reflectivity dBZ values range from -35 to -25 with the median values of \sim -25 dBZ, except for lower
557 bottom regions of the cloud (normalized height, $H_i < 0.2$). The nearly constant median values with

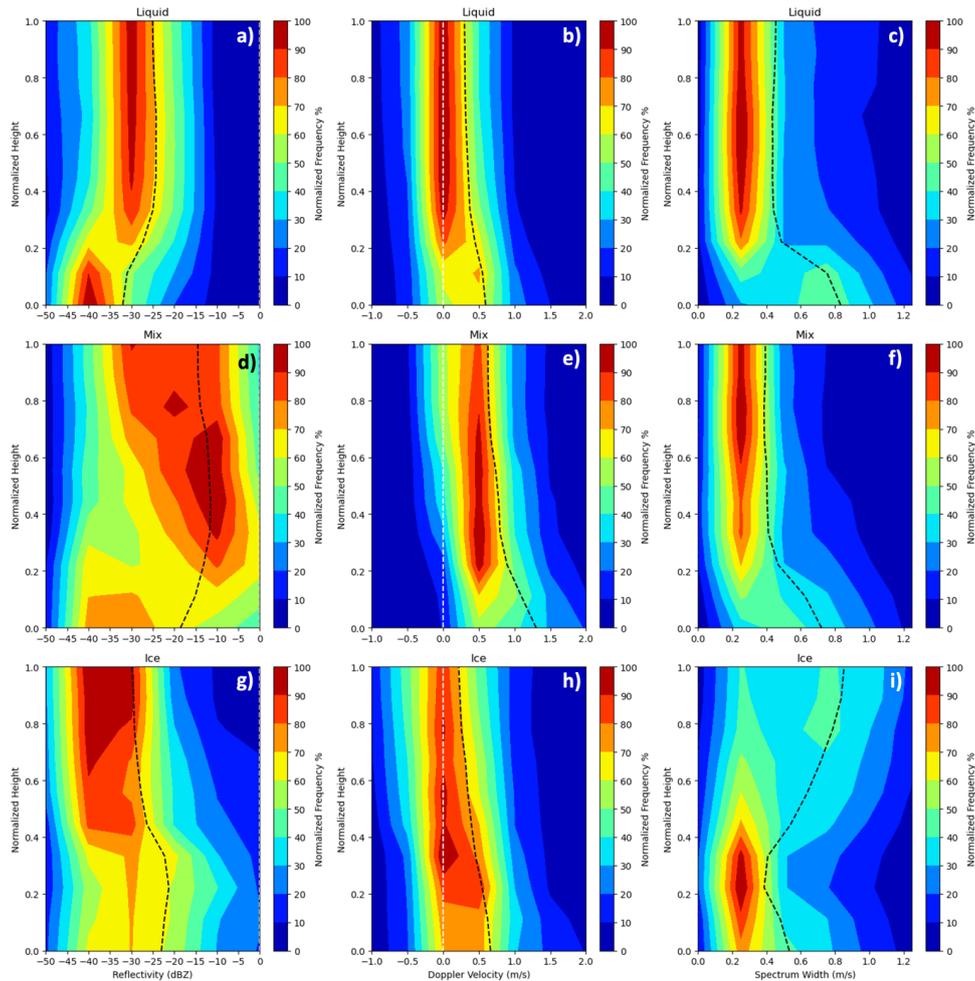


558 height, and moderate dBZ, V_d and WID, indicate the liquid cloud microphysical properties vary slightly
559 within cloud layer with a moderate range of cloud droplets. The maximum occurrences of V_d and WID
560 for liquid clouds are ~ 0.0 m/s and 0.2 m/s. Much higher V_d and WID at the low bottom regions indicate
561 that there are some large drizzle drops with a broader size distribution, however the number
562 concentrations of these large drizzle drops are not higher enough to significantly contribute radar
563 reflectivity. Based on the aircraft in situ measurements during SOCRATES (Zheng et al. 2024), the
564 cloud droplet and drizzle radii near cloud base are one order of magnitude difference ($7 \mu\text{m}$ vs. $70 \mu\text{m}$),
565 whereas their number concentrations are four orders of magnitude difference (100 cm^{-3} vs. 10^{-1} cm^{-3}).
566 These lower number concentrations may attribute to the lower reflectivity near cloud base in Fig. 10a.
567 Another possible reason to explain the contradicted relationship between radar reflectivity and V_d /WID
568 is not enough liquid samples at the lower bottom regions, which can't be ruled out.

569 Compared to the CFADs of liquid cloud samples, the mixed-phase clouds have a broader and higher
570 radar reflectivity dBZ values with the maximum frequencies occur at ~ -10 dBZ around mid-cloud layer,
571 presumably due to their larger particle size and irregular shape or morphology. Correspondingly, their
572 median values are also much large ($-15 \sim -10$ dBZ), except for the lower bottom regions ($H_i < 0.2$). The
573 CFADs of V_d for mixed-phase clouds mimic the shape of liquid cloud samples but with higher
574 maximum occurrence at ~ 0.5 m/s and their median values increase monotonically from cloud top (\sim
575 0.6 m/s) to cloud base (~ 1.3 m/s), indicating that cloud droplets or ice particles increase from cloud top
576 to cloud base, much faster at the lower bottom regions. Consequently, there are more large drizzle drops
577 or ice particles near cloud base with significant downwelling movement and the prevalence of a broader
578 size distribution of particles. Surprisingly, the CFADs of WID for mixed-phase clouds are similar to
579 those of liquid clouds, but not as broader as liquid clouds at the lower bottom regions. These results
580 suggest that the well-mixed cloud droplets/drizzles and ice particles at the lower bottom regions make
581 particle size broader and larger WID values, but they are not as broader and higher WID as liquid clouds
582 where more both cloud droplets and drizzle drops co-exist near cloud base.

583 For ice clouds, their CFADs of V_d are similar to those of liquid clouds, however, their CFADs of
584 radar reflectivity and WID significantly differ to those of liquid and mixed-phase clouds. Most of radar
585 reflectivity dBZ values range from -45 to -25 at the upper regions of cloud layer with the median values
586 of ~ 30 dBZ. Surprisingly, these ice particles with lower radar dBZ values have a much higher WID
587 value, up to 0.8 m/s, and lower V_d values ($\sim 0-0.2$ m/s). These results indicate that most ice particles
588 for SO low clouds have small particles but with a broader size distribution. The CFADs of ice clouds
589 at the upper regions of cloud layer are consistent to those CFADs of liquid and mixed-phase clouds at
590 the lower bottom regions, suggesting that the lower dBZ regions where small cloud droplets or ice
591 particles are dominant can have a broader size distribution for SO low clouds.

592



593
 594 **Figure 10.** Normalized vertical distributions of radar reflectivity (dBZ), Doppler velocity V_d (m/s)
 595 and spectrum width (m/s) for the classified liquid (a-b), mixed (d-f), and ice (g-i) clouds, during
 596 SOCRATES. Height normalization is determined by $H_r = \frac{H - H_{base}}{H_{top} - H_{base}}$, where the cloud top is
 597 denoted as 1 and base as 0. The median values are represented using the black dashed lines and
 598 the white lines in V_d denote 0 m/s. The colorbar denotes the occurrence frequency (%).

599 V_d and WID are codependent variables as V_d indicates the motion of the hydrometeor samples
 600 moving away or towards the radar, however WID is indicative of the spread or variability in the velocity
 601 distribution. For an example, a positive (negative) V_d represent a downdraft (updraft) motion, but a high
 602 (low) WID indicates a significant variability in the velocities, including greater (lower) turbulence and
 603 wind shear, which can be interpreted as a broader (narrower) size distribution. The regions with high
 604 WID but low V_d can be explained as that the average velocity of the cloud particles within the radar's
 605 sampling volume is low, but with a significant spread or variability in their individual velocities due to
 606 significant turbulence, wind shear, or different particles sizes. Conversely, a high V_d but a small WID
 607 suggests the either large drizzle drops, or ice particles are moving (downward) rapidly but uniformly
 608 with a narrow size distribution.



609 The CFAD plots in Fig. 10(a-i) display noticeable skewness. Generally, the frequency plots are
610 skewed to the right, but in Fig. 10(d), the dBZ frequency for mixed-phase samples is skewed to the left
611 due to the higher reflectivity values observed for mixed-phase clouds. Moreover, the median values
612 (black dashed lines in Fig. 10) are significantly shifted towards higher values of WID and Vd near the
613 cloud base, while they shift towards lower values in dBZ for liquid and mixed phase clouds in Fig. 10(a
614 and d). This phenomenon can be attributed to the majority of cloud droplets exhibiting lower reflectivity
615 yet significantly higher values for spectrum width and Doppler velocity at the estimated cloud base.
616 Contributing factors include lower sample counts, and increased turbulence or wind shear contributing
617 to evaporation of particles around the estimated cloud base. Additionally, this observation also results
618 from the nature of cloud sampling during SOCRATES as demonstrated in Fig. 7(a-c), which introduces
619 greater volatility in recorded datasets due to the proximity of the aircraft to the cloud layers compared
620 to ground-based or satellite remote sensing.

621 5 Summary and Conclusions

622 This study developed a phase detection method using HCR radar and in-situ measurements to determine
623 the cloud phase over the Southern Ocean for low-level clouds sampled during the 15 research flights of
624 the SOCRATES campaign. The macrophysical properties and statistical results for the different types
625 of clouds and their correspondingly classified phases were discussed. Finally, the vertical distribution
626 for each phase-specific radar retrieved parameters was presented. Comparisons of this study with
627 existing literature were also discussed. The following conclusions were finally drawn:

- 628 1. A new method based on radar reflectivity and spectrum width gradient was developed to estimate
629 cloud boundaries and classify cloud types as LOW, MID, and MOL based on the estimated cloud-
630 top and -base heights. LOW-type clouds with H_{base} and H_{top} below 3km were found to be the most
631 prevalent with almost 90% occurrence frequency. Liquid Water Path was calculated for each cloud
632 type using the estimated cloud heights and a merged CDP+2DS LWC measurement, with an
633 uncertainty of around 10 g/m^2 . Average LWP values for LOW, MOL and MID clouds are 96.7 g/m^2 ,
634 109.48 g/m^2 and 27.9 g/m^2 , respectively.
- 635 2. A phase determination method was developed to classify the single-layered low-level (LOW)
636 clouds as liquid, mixed, and ice phases with the occurrence frequencies of 45.4%, 22.2% and 32.5%,
637 respectively. Comparison with the MLR phase detection method by D'Alessandro et al. (2021), and
638 Shupe et al. (2005) and Intrieri et al. (2002) method which used lidar PLDR thresholds, showed
639 that the percentage of liquid clouds classified by this study is ~10 to 20% lower, but ~10 to 15%
640 higher in mixed-phased than the results from other two methods, while the classified ice clouds
641 from this study are ~15% higher than those detected by MLR but ~10% lower than those classified
642 using Shupe. This comparison is quite reasonable, as our method is derived from aircraft
643 measurements and radar observations over SO while the methods developed by Intrieri et al. (2002)
644 and Shupe et al. (2005) were based on ground-based lidar measurements in Arctic regions.
645 Additionally, the MLR method employs a machine learning algorithm trained on in-situ cloud and
646 drizzle droplet measurements (CDP+2DS). Using the classified results in this study as a reference,
647 we tune the existing HSRL PLDR thresholds for SO low-level clouds and have the updated
648 thresholds of PLDR < 0.09 for liquid phase, 0.09-0.18 for mixed phase, and >0.18 for ice phase
649 clouds.
- 650 3. For the low-level clouds from 0 to 3 km, the mixed-phase cloud dominates near cloud base (<1 km)
651 but are well distributed along the vertical cloud layer which could be attributed to large drizzle
652 drops or ice particles. The ice-phase clouds are prevalent from the mid to top cloud level (1-3km),
653 while most of the liquid-phase clouds are located in the lower mid-cloud range (from 500 m to 1
654 km).



655 4. The normalized vertical profiles (CFADs) of radar reflectivity, Doppler velocity (Vd) and spectrum
656 (WID) for each determined cloud phase show that the liquid and ice clouds have the lowest
657 reflectivity values, with median reflectivities of around -30 to -25 dBZ, while mixed-phase clouds
658 have a higher median reflectivity of around -15 to -10 dBZ due to large drizzle drops or ice particles.
659 Higher Doppler velocity and Spectrum Width at the cloud base indicate greater drizzle or particle
660 concentrations with significant downwelling movement and the prevalence of a wider size
661 distribution of particles. The CFADs of ice clouds at the upper regions of cloud layer, lower dBZ
662 values but larger WID values, are consistent to the CFADs of liquid and mixed-phase clouds at the
663 lower bottom regions. These results indicate that small cloud droplets or ice particles (lower dBZ)
664 for SO LOW clouds can have a broader size distribution (large WID).

665 In conclusion, the results presented in this study provide comprehensive statistical and phase-
666 relevant macrophysical properties for the low-level clouds sampled during the SOCRATES campaign,
667 along with presenting new methods to estimate cloud boundaries and determine the dominant cloud
668 phase. These results would improve the current understanding of the low-level Southern Ocean cloud
669 properties and further aid in improving model simulations and better representation of the climate.

670 **Data Availability.** All the data and the relevant instrumentation details (radar-lidar and in-situ) for the
671 NSF SOCRATES campaign used in this study are freely accessible from the EOL data archive
672 <https://data.eol.ucar.edu/dataset/> and the official website
673 https://www.eol.ucar.edu/field_projects/socrates. The MLR cloud phase product dataset is
674 available at <https://doi.org/10.26023/S6WS-G5QE-H113>.

675 **Author contributions.** The idea of this study was discussed by AD, BX, and XD. AD performed the
676 analyses and wrote the paper. AD, BX, XD, and XZ participated in the scientific discussions and
677 provided substantial comments and edits on the paper.

678 **Competing interests.** The contact author has declared that neither they nor their co-authors have any
679 competing interests.

680 **Acknowledgments.** The aircraft measured dataset and the SOCRATES campaign relevant details along
681 with the list of publications are available free to access at
682 https://www.eol.ucar.edu/field_projects/socrates. Special thanks to John D'Alessandro (University of
683 Washington) for helping understand the working of the MLR method for phase determination, Ulrike
684 Romatschke (NCAR) for explaining the radar-lidar constrained fuzzy logic parameters for the cloud
685 and drizzle hydrometeor types, and Christopher J. Webster (NCAR) for helping to troubleshoot and run
686 the XPMS2D software to visualize the 2DS probe imagery. The draft of this paper was briefly proofread
687 using the AI tools Grammarly and ChatGPT for final revisions.

688 **Financial Support.** This work was supported by the University of Arizona's IT4IR TRIF and Provost
689 Investigation funds. The researchers at the University of Arizona were also supported by NSF grant
690 AGS-2031750 at the University of Arizona.

691 References

692 Atlas, R., Mohrmann, J., Finlon, J., Lu, J., Hsiao, I., Wood, R., & Diao, M.: The University of
693 Washington Ice-Liquid Discriminator (UWILD) improves single-particle phase classifications of
694 hydrometeors within Southern Ocean clouds using machine learning, *Atmospheric Measurement
695 Techniques*, 14(11), 7079–7101, <https://doi.org/10.5194/amt-14-7079-2021>, 2021.



- 696 Baker, B., Mo, Q., Lawson, R. P., O'Connor, D., & Korolev, A.: Drop Size Distributions and the Lack
697 of Small Drops in RICO Rain Shafts, *J. Appl. Meteor. Climatol.*, 48, 616–623,
698 <https://doi.org/10.1175/2008JAMC1934.1>, 2009.
- 699 Bodas-Salcedo, A., Hill, P. G., Furtado, K., Williams, K. D., Field, P. R., Manners, J. C., et al.: Large
700 contribution of supercooled liquid clouds to the solar radiation budget of the Southern Ocean, *Journal*
701 *of Climate*, 29(11), 4213–4228, <https://doi.org/10.1175/JCLI-D-15-0564.1>, 2016.
- 702 Cesana, G., & Chepfer, H.: Evaluation of the cloud thermodynamic phase in a climate model using
703 CALIPSO-GOCCP, *Journal of Geophysical Research: Atmospheres*, 118(14), 7922–7937,
704 <https://doi.org/10.1002/jgrd.50376>, 2013.
- 705 D'Alessandro, J. J., Diao, M., Wu, C., Liu, X., Jensen, J. B., & Stephens, B. B.: Cloud phase and relative
706 humidity distributions over the Southern Ocean in austral summer based on in situ observations and
707 CAM5 simulations, *Journal of Climate*, 32(10), 2781–2805, <https://doi.org/10.1175/JCLI-D-18-0232.1>,
708 2019.
- 709 D'Alessandro, J. J., McFarquhar, G. M., Wu, W., Stith, J. L., Jensen, J. B., & Rauber, R. M.:
710 Characterizing the Occurrence and Spatial Heterogeneity of Liquid, Ice, and Mixed Phase Low-Level
711 Clouds Over the Southern Ocean Using In Situ Observations Acquired During SOCRATES, *Journal of*
712 *Geophysical Research: Atmospheres*, 126(11), <https://doi.org/10.1029/2020JD034482>, 2021.
- 713 D'Alessandro, J., Schima, J., McFarquhar, G.: SOCRATES Cloud Phase Product. Version 1.0.
714 UCAR/NCAR - Earth Observing Laboratory [data set], <https://doi.org/10.26023/S6WS-G5QE-H113>,
715 2022.
- 716 Desai, N., Diao, M., Shi, Y., Liu, X., & Silber, I.: Ship-Based Observations and Climate Model
717 Simulations of Cloud Phase Over the Southern Ocean, *Journal of Geophysical Research: Atmospheres*,
718 128(11), <https://doi.org/10.1029/2023jd038581>, 2023.
- 719 Dong, X., Xi, B., Kennedy, A., Minnis, P., & Wood, R.: A 19-Month Record of Marine Aerosol–Cloud–
720 Radiation Properties Derived from DOE ARM Mobile Facility Deployment at the Azores. Part I: Cloud
721 Fraction and Single-Layered MBL Cloud Properties, *J. Climate*, 27, 3665–3682,
722 <https://doi.org/10.1175/JCLI-D-13-00553.1>, 2014.
- 723 Eloranta, E. E.: High Spectral Resolution Lidar, In C. Weitkamp (Ed.), *Lidar: Range-Resolved Optical*
724 *Remote Sensing of the Atmosphere* (pp. 143–163), Springer, https://doi.org/10.1007/0-387-25101-4_5,
725 2005.
- 726 Esselborn, M., Wirth, M., Fix, A., Tesche, M., & Ehret, G.: Airborne high spectral resolution lidar for
727 measuring aerosol extinction and backscatter coefficients, *Applied Optics*, 47(3), 346–358,
728 <https://doi.org/10.1364/AO.47.000346>, 2008.
- 729 Ewald, F., Groß, S., Wirth, M., Delanoë, J., Fox, S., & Mayer, B.: Why we need radar, lidar, and solar
730 radiance observations to constrain ice cloud microphysics, *Atmospheric Measurement Techniques*,
731 14(7), 5029–5047, <https://doi.org/10.5194/amt-14-5029-2021>, 2021.
- 732 Hamilton, D. S., Lee, L. A., Pringle, K. J., Reddington, C. L., Spracklen, D. V., & Carslaw, K. S.:
733 Occurrence of pristine aerosol environments on a polluted planet, *Proceedings of the National Academy*
734 *of Sciences*, 111(52), 18466–18471, <https://doi.org/10.1073/pnas.1415440111>, 2014.
- 735 Hu, Y., Rodier, S., Xu, K., Sun, W., Huang, J., Lin, B., Zhai, P., & Josset, D.: Occurrence, liquid water
736 content, and fraction of supercooled water clouds from combined CALIOP/IIR/MODIS measurements,



- 737 Journal of Geophysical Research: Atmospheres, 115(D4), <https://doi.org/10.1029/2010JD014002>,
738 2010.
- 739 Humphries, R. S., Keywood, M. D., Gribben, S., McRobert, I. M., Ward, J. P., Selleck, P., Taylor, S.,
740 Harnwell, J., Flynn, C., Kulkarni, G. R., et al.: Southern Ocean latitudinal gradients of cloud
741 condensation nuclei, Atmospheric Chemistry and Physics, 21(16), 12757–12782,
742 <https://doi.org/10.5194/acp-21-12757-2021>, 2021.
- 743 Intrieri, J. M., Shupe, M. D., Uttal, T., & McCarty, B. J.: An annual cycle of Arctic cloud characteristics
744 observed by radar and lidar at SHEBA, Journal of Geophysical Research: Oceans, 107(C10), SHE-5,
745 <https://doi.org/10.1029/2000JC000423>, 2002.
- 746 Kang, L., Marchand, R., & Smith, W.: Evaluation of MODIS and Himawari-8 low clouds retrievals
747 over the Southern Ocean with in situ measurements from the SOCRATES campaign, Earth and Space
748 Science, 8(3), e2020EA001397, <https://doi.org/10.1029/2020EA001397>, 2021.
- 749 Kang, L., Marchand, R. T., & Wood, R.: Stratocumulus precipitation properties over the Southern
750 Ocean observed from aircraft during the SOCRATES campaign, Journal of Geophysical Research:
751 Atmospheres, 129(6), e2023JD039831, <https://doi.org/10.1029/2023JD039831>, 2024.
- 752 Kay, J. E., Hillman, B. R., Klein, S. A., Zhang, Y., Medeiros, B., Pincus, R., et al.: Exposing global
753 cloud biases in the community atmosphere model (CAM) using satellite observations and their
754 corresponding instrument simulators, Journal of Climate, 25(15), 5190–5207,
755 <https://doi.org/10.1175/JCLI-D-11-00469.1>, 2012.
- 756 Kay, J. E., Wall, C., Yettella, V., Medeiros, B., Hannay, C., Caldwell, P., & Bitz, C.: Global climate
757 impacts of fixing the Southern Ocean shortwave radiation bias in the Community Earth System Model
758 (CESM), Journal of Climate, 29(12), 4617–4636, <https://doi.org/10.1175/JCLI-D-15-0358.1>, 2016.
- 759 Klein, S. A., Hall, A., Norris, J. R., & Pincus, R.: Low-cloud feedbacks from cloud-controlling factors:
760 A review, Shallow clouds, water vapor, circulation, and climate sensitivity, Springer, 135–157, 2018.
- 761 Korolev, A., & Milbrandt, J.: How are mixed-phase clouds mixed?, Geophysical Research Letters,
762 49(18), e2022GL099578, <https://doi.org/10.1029/2022GL099578>, 2022.
- 763 Lance, S., et al.: Water droplet calibration of the Cloud Droplet Probe (CDP) and in-flight performance
764 in liquid, ice and mixed-phase clouds during ARCPAC, Atmos. Meas. Tech., 3, 1683–1706,
765 <https://doi.org/10.5194/amt-3-1683-2010>, 2010.
- 766 Lawson, R. P., O'Connor, D., Zmarzly, P., Weaver, K., Baker, B., Mo, Q., & Jonsson, H.: The 2D-S
767 (stereo) probe: Design and preliminary tests of a new airborne, high-speed, high-resolution particle
768 imaging probe, Journal of Atmospheric and Oceanic Technology, 23(11), 1462–1477,
769 <https://doi.org/10.1175/JTECH1929.1>, 2006.
- 770 Lawson, R. P., Pilson, B., Baker, B., Mo, Q., Jensen, E., Pfister, L., & Bui, P.: Aircraft measurements
771 of microphysical properties of subvisible cirrus in the tropical tropopause layer, Atmospheric Chemistry
772 and Physics, 8(6), 1609–1620, <https://doi.org/10.5194/acp-8-1609-2008>, 2008.
- 773 Mace, G. G., Protat, A., Humphries, R. S., Alexander, S. P., McRobert, I. M., Ward, J., Selleck, P.,
774 Keywood, M., & McFarquhar, G. M.: Southern Ocean cloud properties derived from CAPRICORN
775 and MARCUS data, Journal of Geophysical Research: Atmospheres, 126(4), e2020JD033368,
776 <https://doi.org/10.1029/2020JD033368>, 2021.



- 777 Marcovecchio, A. R., Xi, B., Zheng, X., Wu, P., Dong, X., & Behrangi, A.: What Are the Similarities
778 and Differences in Marine Boundary Layer Cloud and Drizzle Microphysical Properties During the
779 ACE-ENA and MARCUS Field Campaigns?, *Journal of Geophysical Research: Atmospheres*, 128(18),
780 e2022JD037109, <https://doi.org/10.1029/2022JD037109>, 2023.
- 781 McCoy, D. T., Hartmann, D. L., & Grosvenor, D. P.: Observed Southern Ocean cloud properties and
782 shortwave reflection. Part II: Phase changes and low cloud feedback, *Journal of Climate*, 27(23), 8858–
783 8868, <https://doi.org/10.1175/JCLI-D-14-00288.1>, 2014.
- 784 McCoy, D. T., Burrows, S. M., Wood, R., Grosvenor, D. P., Elliott, S. M., Ma, P.-L., Rasch, P. J., &
785 Hartmann, D. L.: Natural aerosols explain seasonal and spatial patterns of Southern Ocean cloud albedo,
786 *Science Advances*, 1(6), e1500157, <https://doi.org/10.1126/sciadv.1500157>, 2015.
- 787 McFarquhar, G.: Measurements of Aerosols, Radiation, and Clouds over the Southern Oceans
788 (MARCUS) Science Plan, United States, <https://doi.org/10.2172/1253914>, 2016.
- 789 McFarquhar, G. M., Finlon, J. A., Stechman, D. M., Wu, W., Jackson, R. M., & Freer, M.: University
790 of Illinois/Oklahoma Optical Array Probe (OAP) Processing Software. Version 3.1.4, Zenodo [code],
791 <https://doi.org/10.5281/zenodo.1285969>, 2018.
- 792 McFarquhar, G. M., Bretherton, C., Marchand, R. T., DeMott, P. J., Alexander, S. P., Protat, A.,
793 Roberts, G., Twohy, C. H., Toohey, D. W., Siems, S., et al.: New Unique Observations of Clouds,
794 Aerosols and Precipitation over the Southern Ocean: An Overview of SOCRATES and MARCUS, in:
795 Proceedings of the 15th Conference on Cloud Physics/15th Conference on Atmospheric Radiation,
796 AMS, 2018.
- 797 McFarquhar, G. M., Bretherton, C. S., Marchand, R., Protat, A., DeMott, P. J., Alexander, S., Rintoul,
798 S. R., Roberts, G. C., Twohy, C. H., Toohey, D. W., et al.: Airborne, ship- and ground-based
799 observations of clouds, aerosols and precipitation from recent field projects over the Southern Ocean,
800 in: Proceedings of the AGU Fall Meeting, Washington, D.C., USA, 10-14 December 2018, A53D-06,
801 2018.
- 802 McFarquhar, G. M., Bretherton, C. S., Marchand, R., Protat, A., DeMott, P. J., Alexander, S. P.,
803 Roberts, G. C., Twohy, C. H., Toohey, D., Siems, S., et al.: Observations of clouds, aerosols,
804 precipitation, and surface radiation over the Southern Ocean: An overview of CAPRICORN,
805 MARCUS, MICRE, and SOCRATES, *Bulletin of the American Meteorological Society*, 102(4), E894–
806 E928, <https://doi.org/10.1175/BAMS-D-20-0132.1>, 2021.
- 807 McGill, M., Hlavka, D., Hart, W., Scott, V. S., Spinhirne, J., & Schmid, B.: Cloud physics lidar:
808 Instrument description and initial measurement results, *Applied Optics*, 41(18), 3725–3734,
809 <https://doi.org/10.1364/AO.41.003725>, 2002.
- 810 NCAR/EOL HSRL Team: Gulfstream V High Spectral Resolution Lidar (GV-HSRL), UCAR/NCAR
811 - Earth Observing Laboratory [data set], <https://doi.org/10.5065/d67w6976>, 2012.
- 812 NCAR/EOL HCR Team: HIAPER Cloud Radar (HCR), UCAR/NCAR - Earth Observing Laboratory
813 [data set], <https://doi.org/10.5065/D6BP00TP>, 2014.
- 814 NCAR/EOL HCR Team, NCAR/EOL HSRL Team: SOCRATES: NCAR HCR radar and HSRL lidar
815 moments data. Version 3.2, UCAR/NCAR - Earth Observing Laboratory [data set],
816 <https://doi.org/10.5065/D64J0CZS>, 2023.



- 817 Oh, S.-B., Lee, Y. H., Jeong, J.-H., Kim, Y.-H., and Joo, S.: Estimation of the liquid water content and
818 Z-LWC relationship using Ka-band cloud radar and a microwave radiometer, *Meteorological*
819 *Applications*, 25, 423–434, <https://doi.org/10.1002/met.1710>, 2018.
- 820 Qiu, S., Dong, X., Xi, B., and Li, J.-L.F.: Characterizing Arctic mixed-phase cloud structure and its
821 relationship with humidity and temperature inversion using ARM NSA observations, *Journal of*
822 *Geophysical Research: Atmospheres*, 120, 7737–7746, <https://doi.org/10.1002/2014JD023022>, 2015.
- 823 Romatschke, U., Dixon, M., Tsai, P., Loew, E., Vivekanandan, J., Emmett, J., and Rilling, R.: The
824 NCAR Airborne 94-GHz Cloud Radar: Calibration and Data Processing, *Data*, 6, 66,
825 <https://doi.org/10.3390/data6060066>, 2021.
- 826 Romatschke, U., and Vivekanandan, J.: Cloud and precipitation particle identification using cloud radar
827 and lidar measurements: Retrieval technique and validation, *Earth and Space Science*, 9,
828 e2022EA002299, <https://doi.org/10.1029/2022EA002299>, 2022.
- 829 Sassen, K.: Deep Orographic Cloud Structure and Composition Derived from Comprehensive Remote
830 Sensing Measurements, *Journal of Climate and Applied Meteorology*, 23, 568–583,
831 <http://www.jstor.org/stable/26181286>, 1984.
- 832 Sassen, K.: The Polarization Lidar Technique for Cloud Research: A Review and Current Assessment,
833 *Bulletin of the American Meteorological Society*, 72, 1848–1866,
834 <http://www.jstor.org/stable/26228894>, 1991.
- 835 Schima, J., McFarquhar, G., Romatschke, U., Vivekanandan, J., D’Alessandro, J., Haggerty, J., et al.:
836 Characterization of Southern Ocean Boundary Layer Clouds using airborne radar, lidar, and in situ
837 cloud data: Results from SOCRATES, *Journal of Geophysical Research: Atmospheres*, 127,
838 e2022JD037277, <https://doi.org/10.1029/2022JD037277>, 2022.
- 839 Scott, R. D., Krehbiel, P. R., and Rison, W.: The Use of Simultaneous Horizontal and Vertical
840 Transmissions for Dual-Polarization Radar Meteorological Observations, *Journal of Atmospheric and*
841 *Oceanic Technology*, 18, 629–648 [https://doi.org/10.1175/1520-0426\(2001\)018<0629:TUOSHA>2.0.CO;2](https://doi.org/10.1175/1520-0426(2001)018<0629:TUOSHA>2.0.CO;2), 2001.
- 843 Shupe, M. D., Uttal, T., and Matrosov, S. Y.: Arctic Cloud Microphysics Retrievals from Surface-Based
844 Remote Sensors at SHEBA, *Journal of Applied Meteorology and Climatology*, 44, 1544–1562,
845 <https://doi.org/10.1175/JAM2297.1>, 2005.
- 846 Shupe, M. D.: A ground-based multisensor cloud phase classifier, *Geophysical Research Letters*, 34,
847 L22809, <https://doi.org/10.1029/2007GL031008>, 2007.
- 848 Trenberth, K. E., and Fasullo, J. T.: Simulation of present-day and twenty-first-century energy budgets
849 of the Southern Oceans, *Journal of Climate*, 23, 440–454, <https://doi.org/10.1175/2009JCLI3152.1>,
850 2010.
- 851 UCAR/NCAR - Earth Observing Laboratory: NSF/NCAR GV HIAPER Raw 2D-S Imagery. Version
852 1.1, UCAR/NCAR - Earth Observing Laboratory [data set], [https://doi.org/10.26023/9555-DKY0-
853 J604](https://doi.org/10.26023/9555-DKY0-J604), 2018.
- 854 Uetake, J., Hill, T. C. J., Moore, K. A., DeMott, P. J., Protat, A., and Kreidenweis, S. M.: Airborne
855 bacteria confirm the pristine nature of the Southern Ocean boundary layer, *Proceedings of the National*
856 *Academy of Sciences*, 117, 13275–13282, <https://doi.org/10.1073/pnas.2000134117>, 2020.



- 857 Vivekanandan, J., Ellis, S., Tsai, P., Loew, E., Lee, W.-C., Emmett, J., et al.: A wing pod-based
858 millimeter wavelength airborne cloud radar, *Geoscientific Instrumentation, Methods and Data Systems*,
859 4, 161–176, <https://doi.org/10.5194/gi-4-161-2015>, 2015.
- 860 Vivekanandan, J., Ghate, V. P., Jensen, J. B., Ellis, S. M., and Schwartz, M. C.: A Technique for
861 Estimating Liquid Droplet Diameter and Liquid Water Content in Stratocumulus Clouds Using Radar
862 and Lidar Measurements, *Journal of Atmospheric and Oceanic Technology*, 37, 2145–2161,
863 <https://doi.org/10.1175/JTECH-D-19-0092.1>, 2020.
- 864 Wang, Y., Zhang, D., Liu, X., and Wang, Z.: Distinct contributions of ice nucleation, large-scale
865 environment, and shallow cumulus detrainment to cloud phase partitioning with NCAR CAM5, *Journal*
866 *of Geophysical Research: Atmospheres*, 123, 1132–1154, <https://doi.org/10.1002/2017JD027213>,
867 2018.
- 868 Wang, Z., and Sassen, K.: Cloud Type and Macrophysical Property Retrieval Using Multiple Remote
869 Sensors, *Journal of Applied Meteorology*, 40, 1665–1682, [https://doi.org/10.1175/1520-0450\(2001\)040<1665>2.0.CO;2](https://doi.org/10.1175/1520-0450(2001)040<1665>2.0.CO;2), 2001.
- 871 Wang, Z., Wechsler, P., Kuestner, W., French, J., Rodi, A., Glover, B., Burkhart, M., and Lukens, D.:
872 Wyoming Cloud Lidar: instrument description and applications, *Optics Express*, 17, 13576–13587,
873 <https://doi.org/10.1364/OE.17.013576>, 2009.
- 874 Wang, Z., French, J., Vali, G., Wechsler, P., Haimov, S., Rodi, A., Deng, M., Leon, D., Snider, J., Peng,
875 L., and Pazmany, A. L.: Single Aircraft Integration of Remote Sensing and In Situ Sampling for the
876 Study of Cloud Microphysics and Dynamics, *Bulletin of the American Meteorological Society*, 93,
877 653–668, <https://doi.org/10.1175/BAMS-D-11-00044.1>, 2012.
- 878 Wu, P., Dong, X., and Xi, B.: A Climatology of Marine Boundary Layer Cloud and Drizzle Properties
879 Derived from Ground-Based Observations over the Azores, *Journal of Climate*, 33, 10133–10148,
880 <https://doi.org/10.1175/JCLI-D-20-0272.1>, 2020.
- 881 Wu, P., Dong, X., Xi, B., Tian, J., and Ward, D. M.: Profiles of MBL cloud and drizzle microphysical
882 properties retrieved from ground-based observations and validated by aircraft in situ measurements over
883 the Azores, *Journal of Geophysical Research: Atmospheres*, 125, e2019JD032205,
884 <https://doi.org/10.1029/2019JD032205>, 2020.
- 885 Wu, W., and McFarquhar, G.: NSF/NCAR GV HIAPER 2D-S Particle Size Distribution (PSD) Product
886 Data. Version 1.1, UCAR/NCAR - Earth Observing Laboratory, <https://doi.org/10.26023/8HMG-WQP3-XA0X>, 2019.
- 888 Wu, W., and McFarquhar, G. M.: On the Impacts of Different Definitions of Maximum Dimension for
889 Nonspherical Particles Recorded by 2D Imaging Probes, *Journal of Atmospheric and Oceanic*
890 *Technology*, 33, 1057–1072, <https://doi.org/10.1175/JTECH-D-15-0177.1>, 2016.
- 891 Xi, B., Dong, X., Minnis, P., and Khaiyer, M. M.: A 10 year climatology of cloud fraction and vertical
892 distribution derived from both surface and GOES observations over the DOE ARM SPG site, *Journal*
893 *of Geophysical Research*, 115, D12124, <https://doi.org/10.1029/2009JD012800>, 2010.
- 894 Xi, B., Dong, X., Zheng, X., and Wu, P.: Cloud phase and macrophysical properties over the Southern
895 Ocean during the MARCUS field campaign, *Atmospheric Measurement Techniques*, 15, 3761–3777,
896 <https://doi.org/10.5194/amt-15-3761-2022>, 2022.



- 897 Zaremba, T. J., Rauber, R. M., McFarquhar, G. M., Hayman, M., Finlon, J. A., and Stechman, D. M.:
898 Phase characterization of cold sector Southern Ocean Cloud tops: Results from SOCRATES, *Journal*
899 *of Geophysical Research: Atmospheres*, 125, e2020JD033673, <https://doi.org/10.1029/2020JD033673>,
900 2020.
- 901 Zhao, L., Zhao, C., Wang, Y., Wang, Y., and Yang, Y.: Evaluation of cloud microphysical properties
902 derived from MODIS and Himawari-8 using in situ aircraft measurements over the Southern Ocean,
903 *Earth and Space Science*, 7, e2020EA001137, <https://doi.org/10.1029/2020EA001137>, 2020.
- 904 Zhao, X., Liu, X., Burrows, S., DeMott, P. J., Diao, M., McFarquhar, G. M., Patade, S., Phillips, V.,
905 Roberts, G. C., Sanchez, K. J., et al.: Important ice processes are missed by the Community Earth system
906 model in Southern Ocean mixed-phase clouds: Bridging SOCRATES observations to model
907 developments, *Journal of Geophysical Research: Atmospheres*, 128, e2022JD037513,
908 <https://doi.org/10.1029/2022JD037513>, 2023.
- 909 Zheng, X., Dong, X., Xi, B., Logan, T., and Wang, Y.: Distinctive aerosol-cloud-precipitation
910 interactions in marine boundary layer clouds from the ACE-ENA and SOCRATES aircraft field
911 campaigns, *EGUsphere*, 2023, 1–45, <https://doi.org/10.5194/egusphere-2023-2608>, 2023.