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Key Points:
• Mixed-phase clouds are identified with CALIPSO data over the Southern Ocean
• The occurrence frequency of ice-containing low clouds increases in the Southern Ocean when the occurrence of mixed-phase clouds is considered
• New phase thresholds identify a strong association between ice precipitation and mixed-phase layers in low clouds over the Southern Ocean

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Abstract Supercooled liquid clouds are an important component of the albedo of the Southern Ocean (SO). While ice phase occurrence in liquid-dominant clouds (hereafter mixed phase) at temperatures warmer than the homogeneous freezing point is rare in the SO, the processes that create mixed-phase clouds are not understood. Using data from the CALIPSO lidar, we reconsider the thresholds of layer-integrated depolarization ratio and layer-integrated attenuated backscatter that are used to diagnose the phases of fully attenuating cloud layers. We argue that liquid-only clouds have understood physical bounds to these thresholds allowing for unique identification of layers that are not consistent with the presence of single-phase liquid tops. Compared to the original phase algorithm the application of these physically constrained thresholds results in a ~70% increase in mixed phase during the annual cycle considered. Combining the CALIPSO data with CloudSat data, mixed-phase clouds seem to typically cooccur with precipitation implying secondary ice forming processes.

1. Introduction

The lidar on the CALIPSO satellite (CALIOP, Winker et al., 2009) is uniquely capable of sensing the phase of cloud condensate near the tops of cloud layers because nonspherical ice particles depolarize scattered laser light while spherical liquid droplets do not (Platt et al., 1978). Hu (2007) and Hu et al. (2009, hereafter H09) developed the physical basis for the phase discrimination algorithm that has been applied to the CALIPSO data set.

In comparison of statistics of thermodynamic phase derived from CALIOP, the parameterizations that cause phase transitions between the liquid and ice phases in models seem to be too aggressive in forming ice (Cesana et al., 2015). It is thought that the simulated high bias in absorbed solar radiation over the Southern Ocean (SO) (Frey & Kay, 2018; Trenberth & Fasullo, 2010) is related to model bias in the phase partitioning within supercooled liquid clouds (Bodas-Salcedo et al., 2016). Once the precipitation process initiates in a mixed-phase environment, ice-phase precipitation depletes the cloud quickly. This effect is demonstrated using a mesoscale model by Vergara-Temprado et al. (2018) who compare simulations of SO cloud systems using traditional ice nucleating aerosol particle (INP) concentrations (Bigg, 1973) with INP concentrations from more recent measurements (DeMott et al., 2010) that are much lower. The simulations show that the lower INP result in more persistent clouds and significantly higher albedo consistent with observations. McCluskey et al. (2018) analyzed the first INP data collected over the Southern Ocean since the 1970s and show that even the INP concentrations reported in DeMott et al. (2010) may be high.

Climate model experiments have also been conducted that relax the cloud phase statistics to those implied by the H09 product. These experiments resulted in a reduction of the solar radiation bias (e.g., Grise & Polvani, 2015; Kay et al., 2016) yet also resulted in larger climate sensitivity (Tan & Storelombo, 2016) although coupled model simulations mitigate the high climate sensitivity (Frey & Kay, 2018) somewhat.

Since the phase determination in the CALIPSO product has fundamental implications for our understanding of phase partitioning in SO clouds, we take a closer look at the thresholds suggested in H09. We were motivated to conduct this study by noting that the H09 thresholds seem to lie far from clouds that appear to be obviously liquid. We wondered what the properties of the intervening clouds might be and whether new thresholds could be established that separate liquid water from mixed-phase clouds.
2. Method

The basis for the CALIPSO phase algorithm was developed from early work by Platt (1973) and Sassen (1974). For a space-based lidar like CALIPSO with footprints on the order of 90 m, multiple scattering in liquid clouds increase liquid depolarization. Therefore, Hu et al. (2007) devised a method based on a combination of Monte Carlo modeling and observations where, for fully attenuating layers, they show that the predominant phase of the scatterers cause observations to reliably occupy particular regions of the conditional probability space described by the layer integrated depolarization ratio (δ) and the layer integrated attenuated backscatter (γ') where $\delta = \int_{\text{top}}^{\text{base}} \beta_{\parallel}(r)dr / \int_{\text{top}}^{\text{base}} \beta_{\perp}(r)dr$ and $\gamma' = \int_{\text{top}}^{\text{base}} \beta_{\perp}(r) + \beta_{\parallel}(r)dr$ and β is the copolarized (||) and cross polarized (⊥) attenuated backscatter cross section with units of sr$^{-1}$ km$^{-1}$.

In Figure 1 we show how opaque liquid water clouds disperse in this δ–γ' space where they occupy a fairly narrow region. This behavior can be understood by considering a straightforward relationship between γ' and δ. Following Platt et al. (1999) and Hu et al. (2007), defining $\eta = \left(\frac{1-T}{1+T}\right)^2$ as the multiple scattering factor, $\eta S = \frac{1-T^2}{2\gamma'}$, where $T$ is the transmissivity of the layer and $S$ is the ratio of extinction (σ) to β (hereafter the lidar ratio). For clouds composed of liquid water droplets like those in Figure 1, $S_c$ is bounded between 17 and 19 (Hu et al., 2006; O’Connor et al., 2004; Pinnick et al., 1983). For fully attenuating water clouds where $T = 0$, the boundedness of $S_c$ significantly constrains the relationship between γ' and δ with the natural variability caused by droplet size distribution (DSD) characteristics.

We consider how $r_c$ could be related to $S_c$ (see also Li et al., 2010). We use ~7,000 two-second averaged water cloud DSDs collected by aircraft during the Rain In Cumulus Over the Ocean (RICO) campaign (Rauber, 2006) to which modified gamma distributions were fit (Mace et al., 2016). From these DSDs we calculate σ and β at 532 nm following the basic methodology outlined in O’Connor et al. (2004) where the DSDs are integrated numerically as a function of diameter using the extinction and backscatter efficiencies derived from Mie theory (Bohren & Huffman, 1983). To minimize the resonance effects in the backscatter efficiency (see O’Connor et al., 2004, their Figure 2), we use approximately 275,000 backscatter efficiencies logarithmically distributed in wavenumber between wavenumbers of 0.1 and 100,000 in the integrations of each DSD. The 7,000 DSDs were then binned by $r_c$ between 5 and 25 μm and the mean $S_c$ calculated in each 1 μm size bin. The result is shown in Figure 2 where a regression of $r_c$ as a function of $S_c$ is shown.

There is a linear relationship between $r_c$ and $S_c$ at 532 nm although the dynamic range in $S_c$ is limited. The assumption of O’Connor et al. (2004) that $S_c$ is essentially constant in a practical sense for real measurements is reasonable since calibrating an elastic lidar sufficiently to distinguish among this range of $S_c$ would be difficult. Our point here is to demonstrate that the physical bounds of $S_c$ lie between roughly 19.5 where a hard physical limit exists as $r_c$ becomes small and roughly 16 for $r_c$ of ~40 μm. Obviously, the lower bound for $S_c$ is not fixed as large droplets can exist but are not long-lived in nature. A rough mean $r_c$ for nonprecipitating liquid clouds in nature is on the order of 10 μm where a value of $S_c$ of 18.7 is given by our regression. O’Connor et al. (2004) report a mean value of 18.8 ± 1.

Using the regression relationship in Figure 2, we overlay contours of $r_c$ in Figure 1. The CALIPSO water cloud data are mostly constrained by the physically reasonable bounds of $r_c$. We note that the 8–40 μm contours contain the majority (84%) of the water cloud measurements with a small fraction of points lying at
Figure 2. The liquid water $r_e$ (microns) as a function of lidar ratio ($S_L$). The points show binned values of $r_e$ and the red line shows the regression relationship in the inset, which is $r_e = 169.72 - 8.53S_L$.

larger $r_e$ and a small fraction of observations at smaller $r_e$. By extrapolation we find that 0.3% of the observations imply a negative $r_e$.

Our point is that since the majority of liquid-certain cloud observations lie within physically understood $\delta$–$\gamma$ boundaries, then it is reasonable to assume, with quantifiable uncertainty, that CALIPSO observations at temperatures colder than freezing that lie outside of the physically reasonable boundaries of the liquid-certain domain are likely due to the presence of ice phase hydrometeors mixed with liquid water droplets. As described by Hu et al. (2007), the upper left of the $\delta$–$\gamma$ space is occupied by randomly oriented ice crystals (hereafter ROI) that tend to depolarize the lidar beam while the lower right of the $\delta$–$\gamma$ space is occupied by horizontally oriented ice crystals (hereafter HOI) that cause specular reflections that do not depolarize but have very large $\beta$. We place proposed thresholds as the dashed red and dashed green lines in Figure 1 suggesting that observations that exist between the dashed and solid lines in subfreezing conditions are not consistent with single-phase liquid water but are likely due to the presence of ice phase hydrometeors occurring simultaneously with water droplets. The placement of the dashed red line is somewhat ambiguous due to the outliers in Figure 1 noted earlier. We place that threshold near where the extrapolation of $r_e$ becomes less than 0. We assume that a false positive occurrence rate in the mixed-phase regions of the phase diagrams would be similar to the frequency of occurrences of outlying measurements for warm clouds. In the upper left quadrant between the dashed red and solid lines we find that a false positive error rate would be 0.3% of the total water cloud observations. On the opposite side there are fewer occurrences beyond the dashed green line where measurements in this space would be due to oriented ice crystals, with a false positive rate of less than 0.01%.

Thus, we argue that fully attenuating hydrometeor layers with layer tops colder than freezing that produce $\delta$ and $\gamma$ between the thresholds marked by the dashed lines and the solid lines of the original phase algorithm have a less than 0.3% probability of being from purely liquid water clouds and likely contain some mixture of ice and liquid hydrometeors.

3. Results

Our goal is to better characterize the occurrence of mixed-phase clouds over the SO. Hereafter, reference to mixed-phase means that the $\delta$–$\gamma$ signatures are inconsistent with the layer top being composed of single-phase liquid as defined above. We conditionally sample the data including single-layer, fully attenuating, oceanic observations between 40°S and 65°S between August 2006 and July 2007 when the CALIPSO lidar was pointing at nadir (0.3°). We also require the layers to have measured bases below 2 km to ensure that they are based in the marine boundary layer (MBL) and have layer top temperatures colder than freezing and warmer than $-40^\circ$C and $-20^\circ$C. We use $-40^\circ$C to represent the homogeneous freezing point and $-20^\circ$C as a reference temperature used for INP activation studies (i.e., McCluskey et al., 2018). We do not attempt to distinguish between ice-only and mixed-phase occurrence here although cursory analysis suggests that the original H09 thresholds are reasonable demarcations. Given our temperature thresholds, we assume that layers outside of the liquid-certain $\delta$–$\gamma$ thresholds will be mixed phase. In addition, we use coincident CloudSat radar (Tanelli et al., 2008) and CALIPSO lidar measurements from the data product described by Mace and Zhang (2014). Layers are separated by precipitation occurrence (layer maximum radar reflectivity $>-15$ dBZ), and by the geometric thickness of the CloudSat-CALIPSO merged columns using $<1$, 1–3, and 3–5 km. For MBL-based clouds, separation by layer thickness tends to separate thin stratiform layers from shallow cumuliform clouds that exist mostly in the MBL while the 3–5 km depth range often includes more vigorous convection. Focusing on Table 1, we find that approximately 6 M layers meet the criteria for analysis with just over half of the layers in the 1–3 km thickness range. The 3–5 km layers were rarer at 14% while geometrically thin ($<1$ km) layers comprised about one third of the columns that met our criteria. Eighty-six percent of the $<1$ km layers were nonprecipitating with rare mixed-phase
occurrence. By contrast, the >1 km thickness layers were mostly precipitating (72% and 97% for 1–3 and 3–5 km, respectively). Mixed-phase occurrence was noted in 6% of the 1–3 km layers, while 23% of the less numerous 3–5 km layers were diagnosed to be mixed phase. We also examined statistics for layers that were warmer than −20°C and found that most frequencies of occurrence of mixed phase were

Table 1
Occurrence Statistics of Fully Attenuating Oceanic Columns Analyzed Between 40°S and 70°S Between December 2006 and November 2007

|                | Fully attenuating single layers (warmer than −40°C) |
|----------------|-----------------------------------------------------|
|                | 5,905,100                                           |
| 0–1 km thickness|                                                    |
| Precipitating  | 996,570 (0.32)                                      |
| Nonprecipitating| 8,618,370 (0.86)                                    |
| 1–3 km thickness|                                                    |
| Precipitating  | 1,733,050 (0.55)                                    |
| Nonprecipitating| 4,733,300 (0.55)                                    |
| 3–5 km thickness|                                                    |
| Precipitating  | 433,450 (0.14)                                      |
| Nonprecipitating| 12,415 (0.03)                                      |

Note. Precipitating layers are those layers with column maximum radar reflectivity factor from CloudSat in excess of −15 dBZe. The values in parentheses show the fraction of that quantity relative to the total in the relevant row above. The bracketed fractions in the bottom row show the fraction of ice phase occurrences that have scattering signatures of horizontally oriented ice crystals.

Figure 3. As in Figure 1 without r₉ contours. The layer top temperatures, top heights, and thicknesses of layers are shown above each plot. The insets show the numbers of layers that lie between the dashed lines (water) and between the dashed and solid lines (mix).
similar with the exception of 3–5 km layers that had a mixed-phase frequency of 0.15 with 0.85 of those in the HOI category.

Figure 3 shows how the precipitating layers are distributed within the δ–γ’ space in various layer top temperature ranges. Supercooled single-phase liquid layers remain predominant. Examining first the top row that shows 0°C to −40°C and 0°C to −20°C range plots and accounting for a conservative 0.5% false alarm rate, the mixed-phase ROI space more than doubles the occurrence of such layers compared to the original phase thresholds in the 0°C to −40°C range and increase the ROI occurrence by a factor 8 in the 0°C to −20°C range. In the HOI category, the false alarm rate is lower. However, the occurrence frequency in the mixed-phase HOI region is fractionally lower than the number of layers that lie beyond the original HOI phase line as compared to ROI. We take this to signify the dominance of the specular reflection when HOI hydrometeors are present. However, by accounting for the mixed-phase HOI region, the occurrences of mixed-phase layers in the HOI category increases by approximately 50% over the occurrence frequency using the previous H09 thresholds. Overall, the new thresholds causes the occurrence frequency of ice hydrometeors in MBL-based clouds over the SO to increase by ~70% in the 0°C to −40°C range.

In the bottom row of Figure 3, we consider −20°C to −40°C and separate by precipitation occurrence. At these colder temperatures, only 30% of the precipitating layers are diagnosed to be mixed phase. Nonprecipitating layers, have δ–γ’ signatures that suggest liquid tops even at these cold temperatures. The number of mixed-phase occurrences in nonprecipitating columns are insignificant relative to false alarms. This result demonstrates a strong coupling between ice occurrence and precipitation-sized hydrometeors within these supercooled cloud layers.

We next examine the zonally averaged occurrence frequencies (Figure 4). The HOI frequency (Figure 4b) broadly replicates the latitudinal distribution (Figure 4a). The new thresholds increase the HOI by about approximately 50% at all latitudes. The ROI occurrence has more interesting zonal variability. Even accounting for the false alarm rate, which is roughly 10% of the total ROI layers that are mixed phase, we find that the occurrence of ROI layers remains nearly 0 south of 60°S but then increases with latitude in relative occurrence reaching a maximum near 45°S. The overall mixed-phase occurrence increases
steadily with latitude reaching a maximum of ~10% of all layers considered in this temperature range at 45°S. For 3–5 km layers (not shown), the mixed-phase occurrence of HOI layers remains at 15% at all north of 70°S with ROI layers increasing from 0 at 55°S to 5% at 45°S. A seasonal cycle in mixed-phase clouds is evident in Figure 4d with occurrence at a minimum in summer and a maximum in winter. The transition seasons seem asymmetrical with autumn (March–May, MAM) indistinguishable from winter and spring (September–November, SON) indistinguishable from summer during this annual cycle.

4. Summary and Discussion

We argue that γ' and δ associated with a physically constrained $S_r$ in liquid-only clouds allows us to establish thresholds that separate liquid-only layers from layers that are not consistent with single-phase liquid clouds. Theoretically and empirically, we demonstrate that observations at subfreezing temperatures that lie between the dashed and solid lines in Figure 1 are physically inconsistent with liquid-only clouds and, in all likelihood, contain some amount of nonspherical ice hydrometeors that cause the scattering signatures to depart from that of single-phase liquid. The false positive rates within the mixed-phase regions are less than 0.5% in the ROI region and less than 0.01% in the HOI portions of the phase diagram (Figure 1).

By separating cloudy profiles into what is reasonably certain to be liquid-topped and those that are likely mixed phase and by combining the CALIPSO data with CloudSat and further segregating by layer thickness, precipitation occurrence, and layer-top temperature, we obtain a much more complete picture of the occurrence of mixed phase in MBL-based clouds over the SO during the annual cycle considered. The occurrence of mixed-phase layers between 0°C and −40°C increase by ~70% when using the new δ- γ' thresholds although the overall occurrence is still dominated by single-phase liquid layers. The occurrence of mixed-phase layers is observed to be a strong function of the thickness of the layers, their temperatures, and whether or not they are precipitating. Layers that were not precipitating according to CloudSat were mostly liquid-phase regardless of layer thickness. Layers that had thicknesses of less than 1 km were rarely precipitating and rarely diagnosed to be mixed phase. Examining precipitating MBL-based layers with temperatures between −20°C and −40°C, we found that ~25% of the layers were diagnosed to have mixed-phase lidar scattering signatures. On the other hand, even at these cold temperatures, layers that did not have column maximum dBZe in excess of −15 produced lidar scattering signatures that lie firmly in the single phase liquid space of the phase diagram. The occurrence of mixed-phase seems always to be coincident with precipitation in these layers. This finding links precipitating ice hydrometeor occurrence with the processes that would tend to cause rapid depletion of liquid water in these supercooled clouds.

We find an interesting latitudinal and seasonal dependence of mixed-phase occurrence in supercooled MBL clouds over the SO during this annual cycle. Overall, mixed-phase occurrence in precipitating layers with thicknesses >1 km increases roughly monotonically toward lower latitudes. There is a clear minimum in mixed-phase layers around Antarctica and a maximum approaching 10% of all layers colder than freezing by 45°S. Seasonally, the ice phase is more common in winter than summer but these seasonal maxima are led by the preceding transition season although we are not certain of the robustness of the seasonal statistics from year to year.

These results suggest that simple thermodynamic arguments cannot explain the processes involved in the production of the ice phase in supercooled MBL clouds over the SO. With low ice nuclei concentrations (McCluskey et al., 2018), we speculate that secondary ice processes associated with shallow convection plays a prominent role (e.g., Hallet & Mossop, 1974; Korolev et al., 2004, 2018; Mossop et al., 1970). We point to the counterintuitive increase in the occurrence of mixed-phase layers toward lower latitudes and warmer sea surface temperatures (SSTs). Because these ice-bearing layers are nearly always associated with precipitation and their occurrence maximizes over warmer SSTs, secondary ice producing processes in convective clouds are suggested (Koenig, 1963; Lasher-Trapp et al., 2016; Lawson et al., 2015). Assuming that this speculation holds up under further scrutiny, we can also imagine how the formation of ice phase precipitation due to secondary processes would be a positive feedback on the SO climate as warmer SSTs support stronger convective motions in shallow clouds resulting potentially in decreasing cloud fractions and warming of the sea surface due to absorbed solar radiation.
References

Bigg, E. K. (1973). Ice nucleus concentrations in remote areas. Journal of the Atmospheric Sciences, 30(6), 1153–1157. https://doi.org/10.1175/1520-0469(1973)030%3C1153:INCIRAT%3E2.0.CO;2

Bodas-Salcedo, A. K., Hill, P. G., Furtado, K., Williams, K. D., Field, P. R., Manners, J. C., et al. (2016). Large contribution of supercooled liquid clouds to the solar radiation budget of the Southern Ocean. Journal of Climate, 29(11), 4213–4228. https://doi.org/10.1175/JCLI-D-15-0564.1

Bohren, C. F., & Huffman, D. R. (1983). Absorption and scattering of light by small particles, 530 Fp. New York: Wiley.

Cesana, G., Waliser, D. E., Ji, X., & Li, J. (2015). Multimodel evaluation of cloud phase transition using satellite and reanalysis data. Journal of Geophysical Research: Atmospheres, 120, 7871–7892. https://doi.org/10.1002/2014JD022932

DeMott, P. J., Pruppacher, H. R., & Hobbs, P. V. (2010). Predicting global atmospheric ice nuclei concentrations and their impacts on climate. Proceedings of the National Academy of Sciences of the United States of America, 107(25), 11,217–11,222. https://doi.org/10.1073/pnas.0910818107

Frey, W. R., & Kay, J. E. (2018). The influence of extratropical cloud phase and amount feedbacks on climate sensitivity. Climate Dynamics, 50(7-8), 3097–3116. https://doi.org/10.1007/s00382-017-3796-5

Grice, K. M., & Polvani, L. M. (2015). Southern Hemisphere cloud-dynamics biases in CCM5 models and their implications for climate projections. Journal of Climate, 27(15), 6074–6092. https://doi.org/10.1175/JCLI-D-14-00113.1

Hallett, J., & Moseley, S. C. (1974). Production of secondary ice particles during the riming process. Nature, 249(5452), 26–28. https://doi.org/10.1038/249064a0

Hu, Y. (2007). Depolarization ratio-effective lidar ratio relation: Theoretical basis for space lidar cloud phase discrimination. Geophysical Research Letters, 34, L11812. https://doi.org/10.1029/2007GL029584

Hu, Y., Liu, Z., Winker, D., Vaughan, M., Noel, V., Biscio, T., et al. (2006). A simple relation between lidar multiple scattering and depolarization for water clouds. Optics Letters, 31(12), 1809–1811. https://doi.org/10.1364/OL.31.001809

Hu, Y., Vaughan, M., McClain, C., Behrenfeld, M., Maring, H., Anderson, D., et al. (2007). Global statistics of liquid water content and effective number concentration of water clouds over ocean derived from combined CALIPSO and MODIS measurements. Atmospheric Chemistry and Physics, 7(12), 3353–3359. https://doi.org/10.5194/acp-7-3353-2007

Levy, R. C., & Krueger, K. J. (1987). The influence of extratropical cloud phase and amount feedbacks on climate sensitivity. Journal of Geophysical Research: Atmospheres, 27(6), 2429–2445. https://doi.org/10.1175/1520-0469(1987)27<2429:TIAFOT>2.0.CO;2

Lim, J., Hwang, J., Nam, K., & Shim, H. (2011). A new method for retrieval of the extinction coefficient of water clouds by using the tail of the CALIOP signal. Atmospheric Chemistry and Physics, 11, 2903–2916. http://dx.doi.org/10.5194/acp-11-2903-2011

Mace, G. D., & Zhang, Q. (2014). The CloudSat radar-lidar geometrical profile products, (RLGeoProf): Updates, improvements, and selected results. Journal of Geophysical Research, 119, 9441–9462. https://doi.org/10.1002/2013JD021374

Mace, G. D., Avey, S., Cooper, S., Lebsock, M., Tanelli, S., & Dobrowski, G. (2016). Retrieving co-occurring cloud and precipitation properties of warm marine boundary layer clouds with A-Train data. Journal of Geophysical Research: Atmospheres, 121, 4162–4176. https://doi.org/10.1002/2015JD024699

Mossop, S. C., Ono, A., & Wishart, E. R. (1970). Ice particles in maritime clouds near Tasmania. Quarterly Journal of the Royal Meteorological Society, 96, 469–487. https://doi.org/10.1002/qj.4970964910

Murray, S. J., Geoghegan, P. W., & Wexler, A. S. (2001). Observations of ice nucleating particles over Southern Ocean. Geophysical Research Letters, 28, 2249–2252. https://doi.org/10.1029/2000GL012866

Murray, S. J., Geoghegan, P. W., & Wexler, A. S. (2001). Observations of ice nucleating particles over Southern Ocean. Geophysical Research Letters, 28, 2249–2252. https://doi.org/10.1029/2000GL012866

MW0019%3E10.1175%2F1520-0426%2F00%3C0000%3E2.0.CO;2

O'Connor, E. J., Illingworth, A. J., & Hogan, R. J. (2004). A technique for autocalibration of cloud lidar. Journal of Atmospheric and Oceanic Technology, 21(5), 777–786. https://doi.org/10.1175/1520-0426(2004)021%3C0777:ATAFOC%3E2.0.CO;2

Pinnick, R. G., Jennings, S. G., Chylek, P., Ham, C., & Hande, W. T. (1983). Backscatter and extinction in water clouds. Journal of Geophysical Research, 88(C11), 6787–6796. https://doi.org/10.1029/JC088iC11p06787

Platt, C. M. (1973). Lidar and radiometric observations of cirrus clouds. Journal of the Atmospheric Sciences, 31, 1571–1576.

Platt, C. M., Alshire, N. L., & McNice, G. T. (1978). Some microphysical properties of ice cloud from lidar observation of horizontally-oriented crystals. Journal of Applied Meteorology, 17(8), 1220–1224. https://doi.org/10.1175/1520-0450(1978)17<1220:SMPOAF%3E2.0.CO;2

Platt, C. M., Ritter, D. M., & Vaughan, M. A. (1999). Backscatter to extinction ratios in the top layers of tropical mesoscale convective systems and in isolated cirrus from LITE observations. Journal of Applied Meteorology, 38, 1330–1345.

Rauber, R. M. (2006). Rain in shallow cumulus over the ocean; the RICO campaign. Bulletin of the American Meteorological Society, 87, 1912–1919.

Sassen, K. (1997). Depolarization of laser light backscattered by artificial ice clouds. Journal of Applied Meteorology, 36(8), 923–933. https://doi.org/10.1175/1520-0450(1997)036%3C0923:DLBBE%3E2.0.CO;2

This research was supported by NASA Grants NNX15AR17G and NNX13AQ34G.
Tan, I., & Storelvmo, T. (2016). Sensitivity study on the influence of cloud microphysical parameters on mixed-phase cloud thermodynamic phase partitioning in CAM5. *Journal of the Atmospheric Sciences, 73*(2), 709–728. https://doi.org/10.1175/JAS-D-15-0152.1

Tanelli, S., Durden, S. L., Pak, K. S., Reinki, D. G., Partain, P., Haynes, J. M., & Marchand, R. T. (2008). CloudSat’s cloud profiling radar after two years in orbit: Performance, calibration, and processing. *IEEE Transactions on Geoscience and Remote Sensing, 46*(11), 3560–3573. https://doi.org/10.1109/TGRS.2008.2002030

Trenberth, K. E., & Fasullo, J. T. (2010). Simulation of present-day and twenty-first-century energy budgets of the southern oceans. *Journal of Climate, 23*(2), 440–454. https://doi.org/10.1175/2009JCLI3152.1

Vergara-Temprado, J., Miltenberger, A. K., Furtado, K., Grosvenor, D. P., Shipway, B. J., Hill, A. A., et al. (2018). Strong control of Southern Ocean cloud reflectivity by ice-nucleating particles. *Proceeding of the National Academy of Sciences, 115*(11), 2687–2692. https://doi.org/10.1073/pnas.1721627115

Winker, D. M., Vaughan, M. A., Omar, A., Hu, Y., & Powell, K. A. (2009). Overview of the CALIPSO Mission and CALIOP data processing algorithms. *Journal of Atmospheric and Oceanic Technology, 26*(11), 2310–2323. https://doi.org/10.1175/2009JTech1281.1