Comparison of Global and Seasonal Characteristics of Cloud Phase and Horizontal Ice Plates Derived from CALIPSO with MODIS and ECMWF

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ABSTRACT

This study analyzed the global and seasonal characteristics of cloud phase and ice crystal orientation (CTYPE-lidar) by using the Cloud–Aerosol Lidar with Orthogonal Polarization (CALIOP) on board the Cloud–Aerosol Lidar and Infrared Pathfinder Satellite Observations (CALIPSO). A dataset from September 2006 to August 2007 was used to derive the seasonal characteristics. The discrimination scheme was originally developed by Yoshida et al., who classified clouds mainly into warm water, supercooled water, and randomly oriented ice crystals or horizontally oriented ice plates. This study used the following products for the comparison with CTYPE-lidar: (i) the vertical feature mask (VFM) of the National Aeronautics and Space Administration (NASA), (ii) the Moderate Resolution Imaging Spectroradiometer (MODIS), and (iii) European Centre for Medium-Range Weather Forecasts (ECMWF). Overall, the results showed that the CTYPE-lidar discrimination scheme was consistent with the outputs from VFM, MODIS, and ECMWF. The zonal mean water cloud cover in daytime from this study showed good agreement with that derived from MODIS; the slope of the linear regression was 1.06 and the offset was 0.002. The CTYPE-lidar ice cloud occurrence frequency and the ECMWF ice supersaturation occurrence frequency were also in good agreement; the slope of the linear regression of the two products was 1.02 in the temperature range $-60^\circ C \leq T \leq -30^\circ C$. The maximum occurrence frequencies in this study and ECMWF were recognized around $-60^\circ C$ of the equator, with their peak shifted from several degrees north ($-9^\circ$N) in September–November (SON) to south ($-9^\circ$S) in December–February (DJF) and back to north ($-7^\circ$N) in March–May (MAM) and June–August (JJA).

1. Introduction

Cloud phase and ice crystal orientation are among the major factors that determine the radiative effect of clouds. Even at the same wavelength, the complex refraction index differs between water and ice. The phase function of a cloud particle, which determines its scattering characteristics, varies depending on the shape of the particle (Sassen and Liou 1979). Phases and shapes of clouds are also important in retrieving the microphysical properties, such as particle size distribution, complex refraction, and liquid/ice water content, which determine the scattering and absorption properties of clouds. Cho et al. (2008) showed that cloud particle shape/orientation is related to macroscale cloud properties such as cloud depth and cloud layer location; among the cloud classification from International Satellite Cloud Climatology Project (ISCCP), horizontally oriented
ice crystals were prominent in cirrostratus, deep convection, altostratus, and nimbostratus classes. The combination of microphysical and macrophysical characteristics determines the radiative characteristics of clouds. Light scattering models indicate that oriented ice crystals can increase cloud albedo by as much as 40% compared to randomly oriented crystals (Takano and Liou 1989). In addition, the proper treatment of the oriented crystals is needed for accurate retrievals of ice microphysics when the Cloud–Aerosol Lidar and Infrared Pathfinder Satellite Observations (CALIPSO) and CloudSat are used (Okamoto et al. 2010). In other words, horizontally oriented crystals induce very strong specular reflections compared with randomly oriented ice (Iwasaki and Okamoto 2001; Yang et al. 2003).

Furthermore, the orientation of cloud crystals is also important in the determination of cloud lifetime, due to its effect on sedimentation velocity (Heymsfield and Iaquinta 2000; Westbrook 2008).

Despite their impact on the climate system, the effects of cloud phase and shape are not well understood, causing the uncertainties in the applicability of parameterization schemes used in general circulation models (GCMs). Many GCMs assume the coexistence of liquid and ice phases at a certain temperature (typically ranging from 0°C to −40°C), and within this range, they assume the ratio of water and ice based on the empirical equations in each model (DelGenio et al. 1996). Some GCMs use more elaborate algorithms based on their microphysical schemes (Wilson and Ballard 1999; Morrison and Gettelman 2008). These differences in cloud parameterization cause a wide spread in the model results (Ho et al. 1998; Tsushima et al. 2006). Unfortunately, most models also assume that ice crystals are oriented randomly (Takano et al. 1992), in spite of the reported influences of cloud particle shape on radiative forcing (Takano and Liou 1989; Wendisch et al. 2005). This variation leads to uncertainties in GCM outputs, to some extent.

Detailed cloud observations are needed for a more comprehensive understanding of cloud phases and orientation, as well as to evaluate the parameterization schemes in model simulations. Although several ground and in situ observations have been undertaken (Platt et al. 1987; Young et al. 2000; Noel and Sassen 2005), they are still restricted in both time and space. However, recent space missions have allowed us to conduct cloud observations on a global scale (Buriez et al. 1997; Stephens et al. 2002; Winker et al. 2007). CALIPSO carries dual-wavelength depolarization lidar and has been in operation since June 2006, acquiring enough data to show seasonal distinctions of cloud phase and particle shape distribution. The CALIPSO level 2 vertical feature mask (VFM) provides cloud phase and particle shape information. According to Hu et al. (2009), the cloud phase discrimination algorithm in VFM takes two steps: first, they use layer-integrated attenuated backscatter and the layer-integrated depolarization ratio to provide the first identification of randomly oriented ice crystal, horizontally oriented depolarization ratio to separate water from horizontally oriented ice plates. Unfortunately, as this method uses layer-integrated parameters, when clouds are vertically thick, VFM tends to combine different cloud types, such as water with ice, and randomly oriented ice crystals with horizontally oriented ice plates. Furthermore, where ice and water coexist within a thick cloud, VFM tends to switch phases from water to ice (and vice versa) frequently at neighboring profiles. Yoshida et al. (2010, hereinafter YO2010) used CALIPSO level 1B products (version 2) and developed a new algorithm to retrieve a cloud phase and ice particle orientation product (CTYPE-lidar) that was resolved vertically, applying this scheme to one season, from September 2006 to November 2006. In this paper, we used CALIPSO level 1B (version 3.2) data and extended the analysis period to one year, from September 2006 to May 2007, to reveal the seasonal variations of CTYPE-lidar. A few changes from the YO2010 scheme were applied as discussed in section 2. Throughout this paper, we compared CTYPE-lidar with the phase retrieval results from VFM, the results from the Moderate Resolution Imaging Spectroradiometer (MODIS) and the results from the European Centre for Medium-Range Weather Forecasts (ECMWF). We also investigated the global distribution of CTYPE-lidar through annual mean analysis as well as seasonal dependency. It is worth noting that the Polarization and Directionality of the Earth’s Reflectances (POLDER) instruments on board the Polarization and Anisotropy of Reflectances for Atmospheric Sciences Coupled with Observations from a Lidar (PARASOL) have the capability to observe polarization from clouds and are effective for the cloud particle phase determination by their polarization capabilities (Goloub et al. 2000; Riedi et al. 2010). For future study, it may be interesting to extend the analysis in this study to POLDER measurement, as is discussed in recent studies (Zeng et al. 2013).

In section 2, we explain the dataset that was analyzed in this paper, with a case study of the CTYPE-lidar discrimination. In section 3, we discuss the day and night differences in CTYPE-lidar retrieval (section 3a), the dependence of CTYPE-lidar patterns on temperature (section 3b), and the difference of the CTYPE-lidar classification between land and ocean (section 3c). In section 4, we compare the CTYPE-lidar discrimination...
scheme with cloud coverage of VFM and MODIS (section 4a), and with the ice supersaturation frequency of ECMWF (section 4b). Last, we summarize our findings in section 5.

2. Data

2a. CALIPSO

CALIPSO was launched in April 2006 and was joined in a constraining satellite formation called “A-Train.” CloudSat and Aqua are two other members in the formation. A cloud profiling radar (CPR) is on board CloudSat and MODIS is on board Aqua. This enables CALIPSO to conduct synergistic observations with CloudSat and Aqua. In the case of CALIPSO, it carries a 532-nm and a 1064-nm dual-wavelength depolarization lidar called the Cloud–Aerosol Lidar with Orthogonal Polarization (CALIOP). It measures the attenuated backscattering coefficient at 532-nm wavelength as a function of altitude, latitude, and longitude. In addition to detecting the attenuated backscatter intensity, CALIOP also has the capability to receive the depolarization information using an onboard polarization beam splitter to separate the parallel and perpendicular components of the 532-nm wavelength. In this study, we used 532-nm total and perpendicular attenuated backscatter data from CALIPSO level 1B products (version 3.2). Attenuated backscatter profiles at 532 nm were calibrated using background signals observed from 60.3- and 75.3-km altitude (Hostetler et al. 2006). In this study, we used CALIOP data below 20 km, and within this range CALIOP changes resolution: (i) 30-m vertical and 333-m horizontal resolution for altitude below 8.2 km, and (ii) 60-m vertical and 1000-m horizontal resolution between 8.2 and 20 km. Minimum detectable backscatter coefficients for the respective altitude range are shown in Table 1. CALIOP has sufficient sensitivity to detect clouds with optical thicknesses as low as 0.01 (McGill et al. 2007), but it cannot penetrate optically thick clouds. Additional technical information on CALIOP can be found in Winker et al. (2006).

2b. Cloud detection

For cloud detection, we used the masking schemes developed by Hagihara et al. (2010). This cloud mask was originally developed and validated by Okamoto et al. (2007, 2008), using radar and lidar data from observations in the western Pacific Ocean near Japan and in the tropical western Pacific Ocean. Hagihara et al. (2010) adapted this masking algorithm to the CloudSat and CALIPSO observations. Among the four cloud-masking schemes by Hagihara et al. (2010), we used the “C2” mask, which was developed for cloud detection for CALIOP. This masking algorithm consisted of two steps. First, they calculated a threshold for the total attenuated backscattering coefficient, \( \beta_{th}(z, r) \), to discriminate cloud signals from noise originating from aerosol and clear sky (where \( z \) is the altitude of the target bin and \( r \) is the distance of the target bin from the satellite). This discrimination was applied to CALIOP’s original resolution: 30-m vertical and 333-m horizontal resolution for altitudes less than 8.2 km, and 60-m vertical and 1-km horizontal resolution for altitudes over 8.2 km. Then, \( \beta_{th}(z, r) \) was determined to be

\[
\beta_{th} = \frac{\beta_{th,aerosol} + \beta_{th,noise}}{2} - \frac{\beta_{th,aerosol} - \beta_{th,noise}}{2 \tanh (1)}
\]

where

\[
\beta_{th,aerosol} = 10^{-5.25} \text{ [m sr}^{-1}] \quad \text{ and } \quad \beta_{th,noise}(z, r) = [P_m(z, r) + P_n + \sigma_n]r^2.
\]

Equation (1) implies that the threshold values for aerosol and noise were selected to be \( \beta_{th,aerosol} \) and \( \beta_{th,noise} \), respectively, and that the inflection point of Eq. (1), where the sign of the curvature changes, was fixed at the altitude of 5 km. The \( \beta_{th,aerosol} \) was derived from the shipboard observation by Okamoto et al. (2007) in the midlatitudes and further validated in Okamoto et al. (2008) in the tropical western Pacific Ocean. Term \( P_m(z, r) \) in Eq. (3) can be calculated as

\[
P_m(z, r) = \frac{\beta_m(z)}{r^2},
\]

where \( \beta_m(z) \) is the volume molecular backscattering coefficient calculated from ECMWF data (Hostetler et al. 2006). Term \( P_n \) is the residue noise from the sensor,
and $\sigma_n$ is its standard deviation. Term $P_n$ was derived using the five profiles of $P_m(z, r)$ and was averaged horizontally at 19–20-km altitude, and $\sigma_n$ was calculated as the standard deviation of $P_n$. It was assumed that clouds did not occur at that altitude.

The second step was the spatial continuity test. The test was applied at the original CALIOP resolution and was used to exclude spike noise that resulted from the contamination of clouds versus aerosol and noise. Here, 25 bins (5 bins \times 5 bins) around the target bin were considered. If the number of bins classified as “cloud” (i.e., cloud fraction exceeded 0.5) was greater than or equal to 13 bins, then the target bin was classified as “cloud.” After this coherence filter test, the data were averaged so that they were in 240-m vertical and 1.1-km horizontal resolution, identical to the CloudSat resolution. The final C2 criterion took fractional values ranging from 0 to 1.

c. Cloud particle type discrimination

The CTYPElidar classification algorithm used in this study was originally developed by YO2010. In this section, we briefly describe the algorithm and the changes that were made from YO2010.

First, “cloudy” areas were distinguished using the masking scheme described in section 2b. In each cloudy pixel the CTYPElidar was classified in two steps, similar to that of the cloud-masking scheme.

The first step was the discrimination of the cloud particle type using a threshold approach. Two parameters, $\delta$ and $x$, were calculated for cloud pixels. Term $\delta$ is the depolarization ratio at the 532-nm wavelength, which is described as

$$\delta = \frac{\beta_{\text{perp}}}{\beta_{\text{parallel}}} \times 100 \text{ (%)},$$

where $\beta_{\text{perp}}$ and $\beta_{\text{parallel}}$ are the attenuated backscattering coefficients for the 532-nm perpendicular and parallel channels, respectively. Term $\beta_{\text{parallel}}$ is derived by subtracting $\beta_{\text{perp}}$ from the total attenuated backscattering coefficient. In general, horizontally oriented ice plates (2D-plate) give low $\delta$, whereas randomly oriented ice crystals (3D-ice) give larger $\delta$. When single scattering is the dominant process, spherical droplets in liquid water clouds give $\delta$ close to zero. However, in the spaceborne lidar observations, large $\delta$ values are expected for water clouds because of the multiple scattering due to the large footprints of the satellite (Hu et al. 2009; YO2010). The second parameter $x$ was defined as the logarithmic form of the ratio of two successive backscattering coefficients at 532 nm, which can be written as

$$x(R_i) = \log_{10} \left[ \frac{\beta_{\text{total}}(R_i)}{\beta_{\text{total}}(R_{i+1})} \right],$$

where $\beta_{\text{total}}(R_i)$ and $\beta_{\text{total}}(R_{i+1})$ are the attenuated backscattering coefficients of the $i$th and $i+1$th layer, respectively. Assuming that the microphysical properties of the two vertically successive layers are homogeneous, the ratio of attenuated backscattering of two successive layers could be related to the extinction ($\sigma$) of the target layer:

$$\frac{\beta_{\text{total}}(R_i)}{\beta_{\text{total}}(R_{i+1})} = \exp[2\sigma(R_i)\Delta R].$$

From Eqs. (6) and (7), the relationship between of $x$ and $\sigma$ can be obtained:

$$\sigma(R_i) = \frac{1}{2\Delta R \times \log_{10} e} x(R_i).$$

This equation shows that the parameter $x$ can be used as a proxy of extinction at the wavelength of 532 nm in a target cloud layer. If the two vertically successive layers have similar homogeneity, then ice clouds are expected to have a smaller extinction, meaning lower $x$, than water clouds. The vertical inhomogeneity may occasionally produce large $x$, but we try to remove such cases by using the spatial continuity test explained in the next paragraph. Ice clouds showing larger $x$ than water clouds have not been observed.

The second step of the particle type discrimination was the spatial continuity test, which was very similar to the procedure for the cloud-masking scheme. Here, 15 bins (3 vertical bins \times 5 horizontal bins) around the target bin were considered. Then, the particle type that was most prevalent in the 15 bins was assigned to the target bin in the center. If there were more than two types that dominated within the 15 bins, then the target cloud type was assigned in the following order: water, 3D-ice, 2D-plate, mixture, unknown1, and unknown2. Using one month of data (June 2006), the water–to–ice cloud ratio decreased from 18.1% to 16.7% when the preference order was changed to unknown2, unknown1, mixture, 2D-plate, 3D-ice, and water. This showed that even if there were two particle types that predominated, the type assignment did not significantly change the water-versus-ice cloud discrimination. Note that 2D-plate defined in this paper refers to clouds that include quasi-horizontally oriented ice plates. Three-dimensional (3D)-ice is accepted to be included in the 2D-plate category because even a small amount of 2D-plate induces a small depolarization ratio due to its
strong backscatter, and there is a possibility that 3D-ice is included in the volume. Last, the pixels that were classified as “water” and that were above 0°C was further discriminated into “warm water,” and those pixels that were below 0°C were discriminated into “supercooled water.” Consequently, cloud particle types were classified into the following seven categories: warm water, supercooled water, 3D-ice, 2D-plate, a mixture of 3D-ice and 2D-plate, unknown1, and unknown2 (Fig. 1). The mixture of 3D-ice and 2D-plate category is newly introduced to YO2010 in this study. Unknown1 could include all types of clouds. Both unknown1 and unknown2 were negligible from June 2006 to May 2007, at less than 0.2% and 0.04% of total clouds, respectively.

Note that the period we analyzed in this paper was before November 2007 and that the tilt angle of CALIOP was set to 0.3°. After November 2007, the tilt angle changed to 3.0° and the depolarization ratio of those classified as 2D-plate would have increased, which would lead some of the 2D-plate to be classified as 3D-ice when the scheme for 0.3° was applied. The “x,” which is the proxy of the extinction coefficient, should not have changed as much as the change in the depolarization ratio after tilting. Therefore, only the threshold of the depolarization ratio between 2D-plate and 3D-ice would need to be reconsidered when applying the algorithm to data after CALIOP’s tilt angle changed to 3.0°.

Our data processing included two major modifications from YO2010. First, the lidar data (backscattering coefficient, cloud mask, CTYPE-lidar) were reprocessed because of the update of the CALIPSO level 1b data from version 2.01 to version 3.2. Next, we modified the discrimination scheme to introduce the “mixture of 3D-ice and 2D-plate” type to replace the original “unknown 1” type. By using one month of data in September 2006, the fraction of ice (3D-ice and 2D-plate) pixels that were placed above or below the unknown1 pixels was over 92%, and less than 8% for that of the warm or supercooled water pixels. Thus, the type was assumed to contain a mixture of the two ice categories and not to contain water. Consequently, the original unknown2 defined by YO2010 was changed to unknown1. When a pixel of either of the two successive layers was missing, we were unable to calculate x and therefore could not classify its particle type. We assigned the corresponding pixels as the new cloud particle type, unknown2. Figure 1 shows the x–δ planes with the new classification scheme.

d. MODIS, ECMWF, and CloudSat

For MODIS cloud phase data, we used the MODIS auxiliary product (MODIS-AUX), which is a set of data originally from the Aqua/MODIS level 2 product (MYD06_L2). The original phase classification by MODIS used the brightness temperature difference between two thermal infrared bands as well as the ratio for the near-infrared and visible bands (King et al. 2004). Detailed information on MODIS-AUX is given in CloudSat Project (2008). For ECMWF, we used temperature, pressure, and specific humidity profiles from the ECMWF auxiliary product (ECMWF-AUX) provided by the CloudSat team. ECMWF-AUX is an ECMWF dataset that was interpolated to CloudSat bins. ECMWF produces a global analysis for the four synoptic hours of 0000, 0600, 1200, and 1800 UTC each day. The numerical scheme is a TLS11L60 (i.e., triangular truncation, resolving up to wavenumber 511 in spectral space and 60 vertical levels), and the horizontal resolution is 40 km. From the specific humidity data, we calculated relative humidity with respect to ice [defined as $e_{wv}/e_{si}$, where $e_{wv}$ (hPa) is water vapor pressure and $e_{si}$ (hPa) is saturation pressure for ice]. The value for $e_{wv}$ was derived from the equation of state and $e_{si}$ from Marti and Mauersberger (1993). The equation for calculating $e_{si}$ is valid over the range $-273.15°C < T < 0°C$. The detailed description of ECMWF-AUX is presented in Benedetti (2003) and CloudSat Project (2008).

Last, we used the CloudSat radar reflectivity data from the CPR CloudSat geometric profile product (2B-GEOPROF) release R04 (Mace 2007). The resolution of the radar reflectivity was 240 m vertical × 1.1 km horizontal. The minimum detectability of the radar reflectivity factor was approximately −28 dBZ (Miller and Stephens 2001; Stephens et al. 2008).
All the data used in this paper were averaged to the 240-m vertical and 1.1-km horizontal resolution of CloudSat, according to the procedure in Hagihara et al. (2010).

e. Case study of cloud particle phase classification

We first analyzed the same clouds observed by the three sensors (CALIPSO/CALIOP, CloudSat/CPR, and Aqua/MODIS) as a case study (Fig. 2). The observation was made on 13 September 2006 over the Arctic. A large deep cloud system with precipitation can be recognized at higher latitudes (72°–82°N). As expected, CPR was able to detect precipitation, whereas CALIOP was strongly attenuated. On the other hand, at lower latitudes (60°–63° and 65°–68°N), CALIOP detected thin broken clouds that were missed by CPR. This was the first orbit-to-orbit comparison of phase discrimination from MODIS and VFM with CTYPE-lidar (Figs. 2d–f). Because of the differences between active and passive sensors, the CALIOP classification showed the two-dimensional cross sections of clouds, whereas MODIS showed a one-dimensional line along the CloudSat/CALIPSO orbit. The CTYPE-lidar classification showed that the majority of clouds below −20°C were 3D-ice. In this scene, between −20°C and 0°C, the 2D-plate and supercooled water became the dominant CTYPE-lidar, with only a few 3D-ice classifications. Hu et al. (2009) introduced a VFM algorithm to discriminate horizontally oriented plates by using the layer-integrated depolarization ratio and a layer-integrated depolarization ratio. This gave a criterion for layer mean property of horizontally oriented ice. It is worth noting that the scheme in VFM was not designed to provide vertically resolved cloud particle type contrary to the CTYPE-lidar. Thus, VFM water and ice discrimination varied from one record to the next. In addition, because of this vertical integration, there were cases where VFM overestimated the horizontally oriented ice regions, causing the 2D-plate to be registered at low backscattering signals and high depolarization ratios (73°–76°N). In other words, the 2D-plate should have produced larger backscatter and smaller depolarization than 3D-ice does (in Figs. 2b and 2c), but some portion of horizontally oriented ice in VFM does not show such features because of the possible misclassification of randomly oriented ice to horizontally oriented ice. It is also unlikely that some of the 2D-plate existed at temperatures as low as −40°C, as explained above (YO2010). The classifications from our study reflected the fine structure of water, 2D-plate, and 3D-ice in the clouds, and the overall classification showed a good agreement between MODIS phase and CTYPE-lidar in clouds at the high latitudes (67°–68°N and 73°–81°N). Interestingly, this case study also reflected the change in the MODIS phase in the overlapped regions of water clouds and ice clouds. In the highest latitude region (73°–81°N), the ice clouds seemed to be thick enough for MODIS to detect, even where the water clouds existed underneath them. On the other hand, at around 71.5°N, where water and thin ice clouds
Dar observations, Ackerman et al. (2008) showed that MODIS. By comparing MODIS with ground-based lidar observations, Ackerman et al. (2008) showed that MODIS may miss clouds with optical thicknesses less than 0.4. There were a few undetermined MODIS phases where water and ice clouds with similar thicknesses overlapped (71.7°–71.9°N and 76.5°–76.8°N).

3. Cloud particle type patterns

a. Day–night differences

We examined the differences in CTYPE-lidar results between daytime and nighttime. In general, because of the background signals from scattered sunlight, daytime data gave much lower signal-to-noise ratios (SNR) than nighttime (Hunt et al. 2009). Therefore, we expected some confidence of the algorithm to be indicated by the consistent CTYPE-lidar frequencies between day and night, provided that the actual day–night variation was small for clouds observed by CALIPSO (Behrangi et al. 2012).

We investigated the latitude–temperature cross section of three-dimensional cloud occurrence frequencies for day and night from September 2006 to August 2007 (Fig. 3). The three-dimensional cloud occurrence frequency of a CTYPE-lidar was defined as the total number of the CTYPE-lidar event divided by the total number of observations. We called it “three dimensional” cloud occurrence to differentiate from the traditional “two dimensional” cloud coverage. The frequencies were calculated for warm water, supercooled water, 3D-ice, and 2D-plate. The latitude and temperature resolutions were 2.0° and 2.0°C, respectively. Relatively consistent cloud frequencies between day and night were found in warm water, supercooled water, and 2D-plate, although slightly stronger frequencies were observed around the equator at night versus during the day for supercooled water and 2D-plate (~0.02). Differences between daytime and nighttime cloud occurrence frequencies were seen for 3D-ice. Comparisons of the three-dimensional cloud occurrence frequencies of day versus night for each CTYPE-lidar are shown in Fig. 4, showing the quantitative differences in the overall cloud occurrence frequencies regardless of temperature and latitude. Each point in Fig. 4 indicates an annual mean three-dimensional cloud occurrence frequency at a specific latitude and temperature from Fig. 3. Despite the larger background signals in daytime, the scatterplot of water (both warm and supercooled) and 2D-plate showed very good agreement between day and night, suggesting that the large background signals were effectively removed by the algorithms. The slope of the linear regression was 0.90 for warm water, 0.92 for supercooled water, and 1.09 for 2D-plate. In addition, the correlation coefficients were 0.96 for warm water, 0.95 for supercooled water, and 0.99 for 2D-plate. The 3D-ice cloud occurrence frequency during the nighttime was higher than that of daytime as also found in Figs. 3(a-3) and 3(b-3), similar to what was found for total cloud occurrence (figure not shown). If this was due to the misclassification of 3D-ice, then the cloud occurrence frequency of the other classifications should have been higher in the daytime too. Since this was not the case, it was likely due to the degradation of cloud detectability in the daytime from the low signal-to-noise ratio rather than the misclassification in CTYPE-lidar scheme. The total cloud occurrence frequency for VFM was also higher at night than during the day.

We investigated the global mean three-dimensional cloud occurrence frequency for warm water, supercooled water, 3D-ice, and 2D-plate (Table 2). The global mean three-dimensional cloud occurrence frequency of a CTYPE-lidar at nighttime (daytime) was defined as the total number of the CTYPE-lidar events in nighttime (daytime) divided by the total number of observation in nighttime (daytime). The altitude ranged from the surface to about 20 km to derive the global mean three-dimensional cloud occurrence frequency. The global mean three-dimensional cloud occurrence frequency for 3D-ice was 1.6 times higher in nighttime than in daytime (4.1 × 10^{-2} for night and 2.6 × 10^{-2} for day). On the other hand, the difference of the global mean cloud occurrence three-dimensional frequency between nighttime and daytime for warm water, supercooled water, and 2D-plate were lower than that for 3D-ice. The global mean three-dimensional cloud occurrence frequency in daytime was 0.95 times that of nighttime for warm water (2.4 × 10^{-3} for night and 2.5 × 10^{-3} for day), 1.2 times higher for supercooled water (4.8 × 10^{-3} for night and 4.0 × 10^{-3} for day), and 1.04 times higher for 2D-plate (3.2 × 10^{-3} for night and 3.1 × 10^{-3} for day).

b. Dependence of cloud particle type on temperature

The ratio of water and ice particles at a given temperature and atmospheric condition is not well understood. We examined the dependence of the CTYPE-lidar occurrence ratio on temperature (Fig. 5). The occurrence ratio of each CTYPE-lidar at a given temperature was defined as the number of CTYPE-lidar observations divided by the total number of clouds. The annual mean CTYPE-lidar occurrence ratio was calculated from September 2006 to August 2007 at a temperature resolution of 0.25°C. As expected, the water ratio (sum of warm water and supercooled water) tended to increase as
temperature increased, whereas the ice ratio (both 3D-ice and 2D-plate) started to increase at temperatures below 0°C; 50% of the water occurrence ratio was found at about −10°C. Our findings agreed with previous work, such as from ground observations (Shupe et al. 2006) and numerical simulations (Rauber and Tokay 1991), that mixed-phase clouds may exist at temperatures between 0° and −40°C (Rogers and Yau 1989). In addition, the result also agreed with the analysis on the temperature dependency of horizontally oriented plates by Zhou et al. (2013). Our result is consistent with Zhou et al. (2012) in the perspective that the existence of quasi-horizontally oriented plates is higher at warm temperatures over −35°C than at cold temperatures below −35°C. The result from Zhou et al. (2012) may infer that the fraction of 2D-plate contains a relatively small portion in the cloud, as their method used layer-integrated depolarization ratio and attenuated backscatter. Here, we consider the fraction

![Fig. 3. Latitude vs temperature distribution of occurrence frequency for (a-1) warm water in daytime, (a-2) supercooled water in daytime, (a-3) 3D-ice in daytime, (a-4) 2D-plate in daytime; and (b-1) warm water in nighttime; (b-2) supercooled water in nighttime; (b-3) 3D-ice in nighttime; and (b-4) 2D-plate in nighttime from September 2006 to August 2007. Occurrence ratio of a CTYPE-lidar at a given latitude and temperature was defined as the number of CTYPE-lidar events divided by the total number of observations. The latitude resolution was 2.0° and temperature resolution was 2.0°C. Note that the temperature ranges for vertical axes were −40°C < T < 50°C for warm water and −80°C < T < 10°C for all others.](image-url)
of the 2D-plate to be higher if we resolve the layer vertically. Okamoto et al. (2010) showed that ice water content retrieval become overestimated when 2D-plate is not considered. Our scheme may not exactly coincide with previous work on mixed phase clouds because we did not accept the coexistence of water and ice, and only one CTYPE-lidar was accepted in the ideal CloudSat grid box. In our scheme, 3D-ice existed at temperatures over 0°C and these particles may have been due to its transportation from colder temperatures. Furthermore, the errors in temperatures and algorithms may induce the discrepancy between our result and the previous results. Considering that in our classification, dendrites, needles, and columns correspond to 3D-ice, our results agreed with previous findings of the existence of plate crystals with dendrites at $-20^\circ C < T < -10^\circ C$, and with needles and columns being dominant at $-10^\circ C < T < 0^\circ C$ and $T < -20^\circ C$ (Pruppacher and Klett 1997).

c. Land–ocean differences

We examined the latitude–altitude cross section of three-dimensional water and ice cloud occurrence frequency over land and ocean (Fig. 6). Note that water was defined as the sum of warm water and supercooled water, and that ice was defined as the sum of 3D-ice, 2D-plate, and a mixture of 3D-ice and 2D-plate. The definition of the three-dimensional cloud occurrence frequency and the latitude resolution was the same as that in Fig. 3. The altitude resolutions were 240 m. The discontinuity of phase distribution around latitude $-60^\circ$ over land [Figs. 6(a-1) and 6(b-1)] is caused by the small number of sampling due to a lack of land over the Southern Ocean. As mentioned in YO2010, the maximum altitude at which water could be observed depended on the latitude; in general, the maximum altitude became higher as the latitude decreased. This
Arch-like shape of the three-dimensional water occurrence frequency corresponded to the temperature at which supercooled water can exist. YO2010 stated that the water cloud fraction became close to zero (<2%) below −40°C. Very cold water (<−40°C) was not found in either land or ocean in our analysis. Figure 6 illustrates the significant contrast between land and ocean at altitudes below 3 km. The annual mean three-dimensional water cloud occurrence frequency below 3 km over ocean was almost double the frequency over land (3.7 × 10^−2 over ocean and 1.9 × 10^−2 over land). This was considered to be due to the larger supply of water vapor over the ocean compared to the land. In contrast to water, the annual mean ice cloud occurrence did not differ significantly between land and ocean, and below 18 km it was 4.0 × 10^−2 for land and 3.7 × 10^−2 for ocean. Note that more upward air motion over land did not significantly affect the ice cloud occurrence, but it is reported that a distinct difference in ice water content (IWC) was found, with higher IWC over land than over ocean (Okamoto et al. 2010).

4. Comparison with VFM, MODIS, and ECMWF

a. Cloud coverage comparison with VFM and MODIS

Prior to this study, YO2010 studied the global daytime monthly-mean distribution of CTYPE-lidar with the monthly-mean cloud coverage from MODIS level 3 data products (MYD08_M3) from September 2006 to November 2006. In this study, we examined the zonal mean phase coverage of CTYPE-lidar, VFM, and MODIS during the same period (Fig. 7). Here, the cloud coverage corresponds to the traditional two-dimensional cloud occurrence frequency and the zonal mean cloud coverage for water at a latitude that was defined as the total number of water cloud that was observed at the topmost pixels in the topmost layer divided by the total number of the observation profile at the corresponding latitude. The definition is the same for ice and total cloud. Only the topmost pixels were taken into account for CTYPE-lidar and VFM, and only the daytime data were accepted because MODIS retrieves phase classification using the visible channel. Each of the zonal mean values was calculated for water, ice, and total cloud. The water cloud for CTYPE-lidar was defined as the sum of warm water and supercooled water, and the ice cloud was defined as the sum of 3D-ice, 2D-plate, and a mixture of 3D-ice and 2D-plate. The ice cloud for VFM was defined as the sum of randomly oriented ice and horizontally oriented ice. The latitude resolution was 2.0°. The zonal mean cloud coverage for all three schemes were distributed similarly (Fig. 7): (i) the enhancement of ice clouds could be seen in the tropics due to the Hadley cell at about 8°; (ii) the low ice cloud coverage was identified in the subtropical high pressure belt at about −20° and 23°; and (iii) the enhancement of both ice and water clouds was indicated at higher latitudes (about 60°) in the known storm-track regions of both hemispheres. The zonal mean CTYPE-lidar cloud coverage for water was between 0.2 and 0.4, and was in good agreement with MODIS and VFM except at high latitudes, where MODIS seems to have been underestimated. The MODIS ice cloud coverage was much lower than CTYPE-lidar, and this reflected the difference in the cloud detection sensitivity between CALIOP and MODIS. In contrast, the zonal mean VFM cloud coverage was higher than CTYPE-lidar, and one of the reasons for this was suspected to be the horizontal averaging scheme in VFM. To increase the signal-to-noise ratio, VFM extended the contiguous areas of the backscatter signal horizontally to detect a “feature” and then classified it as a cloud or an aerosol (Vaughan et al. 2005), which led to the resultant horizontal resolution of the clouds often reaching 80 km.
addition, recent studies demonstrated that VFM often misclassified noise or aerosols as clouds (Holz et al. 2008; Marchand et al. 2008; Hagihara et al. 2010; Rossow and Zhang 2010). Note that the comparisons in those studies were carried out using CALIOP level 1B version 2 data or earlier. However, the difference between VFM and our results for water in Fig. 7 would infer with the overestimation using level 1B version 3. This can be explained as follows. When our mask was used, there was little difference in the cloud detection (in C2 results) between CALIOP level 1B version 2 and version 3 (Hagihara et al. 2014). Taken together with the work by Rossow and Zhang (2010), where the results of our cloud mask at low level agreed well with ISCCP in daytime when version 2 was used, it is likely that the difference between our findings and VFM in Fig. 7 would be due to the overestimation of low-level clouds in version 3.

We also analyzed the correlation between CTYPE-lidar, VFM, and MODIS by constructing scatterplots of the zonal mean coverage of CTYPE-lidar and VFM versus MODIS, showing the differences in the relationship of VFM and CTYPE-lidar to MODIS (Fig. 8). Each plot in Fig. 8 represents zonal mean cloud coverage at specific latitudes in Fig. 7. For ice clouds, CTYPE-lidar and VFM generally had larger cloud coverage than MODIS, which was thought to be due to the low sensitivity of MODIS to thin cirrus clouds as discussed earlier. CTYPE-lidar had much better ice cloud correlation with MODIS than VFM (correlation coefficient was 0.82 for CTYPE-lidar and 0.27 for VFM). For zonal mean water coverage, CTYPE-lidar and MODIS were in good agreement, and the slope of the linear regression was 1.06. Where MODIS water coverage was lower than CTYPE-lidar, it was likely due to the passive MODIS sensors having difficulty observing clouds, especially at high latitudes over bright surfaces such as snow (Wang et al. 2013), as can be seen in Fig. 7b. On the other hand, when MODIS water coverage was larger than CTYPE-lidar, it was likely due to MODIS classifying the phase as water when water and ice clouds overlapped (cf. Fig. 2). The correlation coefficients for water clouds were better in VFM (0.92) than in CTYPE-lidar (0.88), and VFM had larger cloud coverage than CTYPE-lidar. The linear regressions for CTYPE-lidar and VFM had slopes of 1.06 and 1.20, and the offset was 2.1 × 10⁻³ and 2.5 × 10⁻², respectively.

b. Seasonal characteristics of ice clouds from CALIPSO and supersaturation from ECMWF

Supersaturation is a key parameter in cloud formation. A number of studies (Ovarlez et al. 2000; Tompkins et al. 2007; Rädel and Shine 2010) have compared ice supersaturation from ECMWF with cloud occurrence from in situ measurements and found relatively good agreement. In this paper, the global distribution of ice cloud occurrence was examined using ice supersaturation occurrence derived from ECMWF data.

We compared our classification scheme using ice relative humidity derived from ECMWF data (Fig. 9). The observation was made over the Antarctic Ocean
Ice relative humidity was not calculated at temperatures over 0°C. At temperatures below 0°C, the region where our classification detected clouds roughly matched the region where ice relative humidity was high (over 80%). However, ice relative humidity did not exceed 100% even though our scheme (and VFM) identified cloudy regions. This is likely due to the underestimation of water vapor density when expanding the subgrid-scale water vapor density to the large scale in ECMWF (Tomkins et al. 2007).

We compared the seasonal differences of global three-dimensional ice cloud occurrence frequency obtained by our classification with three-dimensional ice supersaturation occurrence frequency derived from ECMWF data (Fig. 10). The definition of three-dimensional occurrence frequencies was the same as that defined in Fig. 3. Ice cloud occurrence frequency and ice supersaturation occurrence frequency were calculated for each season from September 2006 to August 2007. The latitude and temperature resolutions were the same as in Fig. 3. The definition of the “ice cloud” for this study was the same as that defined in Fig. 7. Overall, the magnitude of zonal mean ice occurrence frequency from our classification was similar to the ice supersaturation frequency of ECMWF. Both of these results showed similar seasonal
characteristics. Large occurrence frequencies of ice were recognized around \(-60^\circ\)C of the equator in all seasons. The location of the maximum ice fraction moved from \(-9^\circ\)N in September–November (SON) to \(-9^\circ\)S in December–February (DJF), and then back to \(-7^\circ\)N during March–May (MAM) and July–August (JJA). This is considered to correspond to the movement of the intertropical convergence zone. In addition, exceptionally low occurrence frequencies of ice supersaturation and cloud frequency could be seen for all temperature ranges around \(15^\circ\) in both hemispheres during DJF, although their magnitudes were much lower, around 0.05 (possibly more strong subduction) at \(15^\circ\)N than at \(15^\circ\)S. Similarly, low occurrence frequencies in both schemes were recognized around \(15^\circ\) in both hemispheres during JJA, although their magnitudes were much lower at \(15^\circ\)S (0.03) than at \(15^\circ\)N. The overall frequency pattern agreed well between the schemes, and they showed similar seasonal dependencies, especially at temperatures colder than \(-20^\circ\)C.

There were also notable differences between the ice fraction detected by our scheme and the ECMWF above \(-20^\circ\)C. Despite their similar seasonal migrations, a relatively high supersaturation frequency could be recognized at high temperatures (above \(-20^\circ\)C) at high latitudes (over 50\(^\circ\) in both hemispheres) in ECMWF. This could be an artifact due to the estimation of ice supersaturation in this study, and it is explained by the frequent occurrence of supercooled water in the corresponding temperature range leading to the overestimation of ice supersaturation (Fig. 10).

In the previous study, YO2010 analyzed the latitude versus temperature distribution of water cloud occurrence ratio (defined as the number of water cloud event divided by the total number of cloud event, implying the “water–ice occurrence ratio”) in SON and showed that the temperature at which the ratio become 0.5 stayed around \(-10^\circ\)C at all latitudes. By extending the period to one year, we found that the temperature at which the ratio becomes 0.5 stayed around \(-10^\circ\)C at all seasons (figure not shown). We also found out that, locally, this fairly high water cloud occurrence ratio was found at temperatures lower than \(-10^\circ\)C (often reaching 0.4 at \(-15^\circ\)C) and that this was distributed symmetrically relative to equator (around 20\(^\circ\)N and 20\(^\circ\)S) in MAM as in SON reported by YO2010, but neither in JJA nor DJF.

We compared the three-dimensional ice cloud occurrence frequency and the three-dimensional ice supersaturation frequency of ECWF for various temperature regions (Fig. 11). Each point represents a frequency at a specific latitude and temperature from September 2006 to August 2007. The latitude and temperature resolutions were 2.0\(^\circ\) and 2.0\(^\circ\)C, respectively. The slope of the linear
regression was low (0.28) when our calculations used the entire temperature range. However, because the estimation of supersaturation at higher temperatures ($T > -20^\circ C$) leads to the overestimation of ice, we restricted the temperature range to $-60^\circ C \leq T \leq -30^\circ C$ and recalculated the linear regression. This improved the agreement, and the slope was 1.02 (figure not shown).

5. Summary

We analyzed the global and seasonal characteristics of the cloud phase and ice crystal orientation, using a CALIPSO dataset from September 2006 to August 2007 and the modified YO2010 cloud particle type scheme. In general, the results showed that the cloud particle type classification method was consistent with the products from VFM, MODIS, and ECMWF.

We first compared daytime and nighttime cloud particle type data to evaluate the classification algorithm. Despite the larger background signals in daytime, differences in cloud occurrence frequency between day and night were small except for 3D-ice, inferring the reliability of our scheme. For 3D-ice, the occurrence frequency was higher in the nighttime than in the daytime,
and this was likely due to the degradation of thin cloud detectability from the low signal-to-noise ratio during the daytime.

We found a significant difference in the annual mean three-dimensional water cloud frequency of occurrence between land and ocean below 3 km, where the majority of water clouds exist. The annual mean three-dimensional water cloud occurrence frequency below 3 km was defined as the total number of the water cloud event below 3 km divided by the total number of the observation below 3 km. Note that we called it “three-dimensional” frequency to differentiate it from the traditional “two-dimensional” cloud coverage that is described in the next paragraph. The three-dimensional water occurrence frequency over the ocean was almost double that of land, with 0.037 over ocean and 0.019 over land. This was likely due to the large supply of water vapor over ocean.

We compared the zonal mean daytime topmost cloud particle type from this study and VFM with zonal mean daytime cloud coverage derived from MODIS for water, ice, and total cloud. Here, the cloud coverage corresponds to the traditional two-dimensional frequency of cloud occurrence. The zonal mean topmost water cloud coverage from this study was between 0.2 and 0.4, and it was in very good agreement with the zonal mean water cloud coverage derived from MODIS except in high latitudes, where MODIS seems to have been underestimated. The slope of the linear regression was 1.06 and there was almost no bias (the offset being 0.002). Furthermore, from the comparison with VFM, it indicated a higher topmost water coverage than our product and MODIS. Ice cloud coverage of the CTYPE-lidar and VFM was larger than that of MODIS. The difference of CTYPE-lidar and VFM was smaller than the difference of MODIS and the two lidar products. This can be naturally understood by the difference in the sensitivity of the instruments.

Future studies should focus on deepening our understanding of the cloud phase characteristics and ice orientation, as well as using cloud particle type classification schemes to evaluate cloud parameterization in global cloud resolving models. The discrimination scheme described here will be adapted to the algorithm for the next generation of spaceborne high-spectral-resolution lidar [atmospheric lidar (ATLID)] on board the Japanese–European mission the Earth Cloud, Aerosol and Radiation Explorer (EarthCARE).

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