Remote Sensing of Ice Water Characteristics in Tropical Clouds Using Aircraft Microwave Measurements

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ABSTRACT

An ice water path retrieval algorithm, using airborne Millimeter-Wave Imaging Radiometer brightness temperatures at 89, 150, and 220 GHz, is developed for tropical clouds. This algorithm is based on the results of radiative transfer model simulations, using in situ ice particle properties measured from aircraft as model inputs. The scattering signatures at the 150- and 220-GHz channels are the primary inputs into the algorithm, while 89-GHz data are used for determining the nonice background radiation. The ice water path is first calculated from each of the 150- and 220-GHz scattering signatures, and then a combination of the two channels is used for the final retrieval, based on the consideration of the different channel sensitivities to the magnitude of the ice water path. The algorithm is evaluated by comparing the retrieved with in situ measured ice water paths for seven cases observed during the Tropical Oceans Global Atmosphere Coupled Ocean-Atmosphere Response Experiment (TOGA COARE). Theoretical analysis shows that the uncertainty due to particle size could be the largest error in the retrievals and this error could be as large as plus or minus 50%. As an application of this algorithm, the ice water path characteristics during TOGA COARE are studied, including assessment of the mean of ice water path, its frequency distribution, and its relationships with cloud-top temperature and liquid water amount. Although tropical clouds are the target of this study, this algorithm could be modified and extended to other climatological regions.

1. Introduction

The amount of condensed water in tropical ice clouds is one of the most important physical parameters in determining the earth’s radiation balance. The reflection of shortwave radiation by ice cloud reduces the solar energy reaching the earth’s surface. High-altitude ice clouds also have a “greenhouse effect” because their cold temperatures permit less infrared radiation to escape to space than under clear-sky conditions. The complex effect of ice clouds on earth’s radiation budget has been discussed by Liou (1986), among many others. The amount and spatial distribution of ice water is an important component in understanding atmospheric circulation systems on a variety of scales (e.g., Hobbs and Rango 1985; Rutledge and Hobbs 1983). Ice water amount generated by deep convection reflects the strength of the convection and the stage in the life cycle of the convective cloud. Knowledge of ice water content is essential to infer cloud vertical structure (e.g., Sheu et al. 1997), which determines the cloud vertical heating profile, and to parameterize ice cloud radiative properties for general circulation models (e.g., Heymsfield and Donner 1990; Ebert and Curry 1992; Fu and Liou 1993).

The studies of ice water amount in tropical clouds have been conducted primarily using aircraft in situ measurement (e.g., Knollenberg et al. 1993; Heymsfield 1993). Recently, Heymsfield and McFarquhar (1996) and McFarquhar and Heymsfield (1996) investigated the microphysical characteristics and radiative properties of tropical cirrus using aircraft-measured data during the Central Equatorial Pacific Experiment (CEPEX). Ice water retrieval from remotely sensed data is a new approach, and most retrieval algorithms are in the development stage. Inoue (1987) demonstrated a technique of using infrared split window information to distinguish cirrus from other clouds. Minnis et al. (1993a) and Minnis et al. (1993b) developed a method to retrieve cirrus cloud properties from satellite-observed visible and infrared data. Han et al. (1996) assessed the effective particle size of ice particles over most parts of the globe using the International Satellite Cloud Climatology Project (ISCCP) dataset. Ice water path (IWP) over the tropical ocean was estimated by Sheu et al. (1997) using multichannel satellite data including visible and infrared data (from ISCCP) and microwave brightness temperatures from the Special Sensor Microwave/Imager (SSM/I). Liu and Curry (1996, 1997) proposed a
method to retrieve ice water path and snowfall rate over high-latitude oceanic regions during winter using Special Sensor Microwave Water Vapor Sounder (SSM/T2) data. They attempted to relate the variations in ice water amount and snowfall rate to synoptic weather systems. A theoretical study was done by Evans and Stephens (1995a,b) to demonstrate the feasibility of retrieving ice water path in thin cirrus clouds using high-frequency microwave observations. Vivekanandan et al. (1991) studied the feasibility of retrieving precipitation-size ice water amount from the SSM/I 85.5-GHz channel using radiative transfer model simulations. While ice water amount is not retrieved directly, many precipitation algorithms utilize ice-scattering signatures to retrieve rainfall rate (e.g., Adler et al. 1993; Grody 1991; Petty 1994).

In this study, we develop an algorithm to retrieve ice water path in tropical ice clouds using the Millimeter-Wave Imaging Radiometer (MIR) data onboard NASA aircraft ER-2 during the intensive observation period of the Tropical Oceans Global Atmosphere Coupled Ocean–Atmosphere Response Experiment (TOGA COARE). Ice water characteristics in the tropical ice clouds will be investigated using these retrievals. Given the paucity of ice water characteristics data, the results of this study could be a valuable supplement to our current knowledge of tropical ice clouds.

2. Data

The primary data sources are from aircraft-borne MIR measurements during TOGA COARE, and aircraft in situ measurements during CEPEX and TOGA COARE. The in situ measurement data are used for ice water path algorithm development and validation.

a. MIR data

MIR is a cross-scan radiometer operating at six frequencies: 89, 150, 183.3 ± 1, 183.3 ± 3, 183.3 ± 7, and 220 GHz (Racette et al. 1996; Wang et al. 1997). The first five channels are similar to those of the SSM/I and T2 on the DMSP (Defense Meteorological Satellite Program) satellites. The three water vapor channels (183.3 ± 1, ±3, ±7) are not used in this study. The MIR scans plus or minus 50° from nadir every 3 s, during which radiance at 57 positions is sampled. The beamwidth for all channels is 3.5°. The MIR was flown for 12 flights on a NASA ER-2 aircraft from 12 January through 24 February 1993 during TOGA COARE. The spatial resolution of the MIR channel is about 1.2 km at nadir when the aircraft flies at an altitude of 20 km. The resolution of brightness temperature is better than 1 K for all channels.

b. Aircraft in situ data

CEPEX microphysical data, collected from 7 March to 5 April 1993 in the tropical Pacific Ocean by a Learjet aircraft, were used for developing the ice water path algorithm. A detailed description of the instrumentation and analysis procedures is given by McFarquhar and Heymsfield (1996). In this study, data measured by the Particle Measuring Systems’ two-dimensional cloud probe (2DC) were used. The minimum detectable size for the 2DC at the aircraft’s traveling speed is about 40 μm. The procedure for calculating particle size and mass from the 2DC images follows Heymsfield et al. (1990), in which a habit and mass are assigned to each particle based on its dimension and area ratio. The data are available from the CEPEX Integrated Data System located at the University of California, San Diego. TOGA COARE microphysical data were measured by a 2D-Grey probe on a DC-8 aircraft during January and February 1993. We used ice water contents produced by the National Center for Atmospheric Research for ice water path algorithm validation purpose in this study (provided by J. Goldstein (1997, personal communication)).

c. Other datasets

Data obtained from the Advanced Microwave Precipitation Radiometer (AMPR) and the Moderate Resolution Imaging Spectroradiometer (MODIS) Airborne Simulator (MAS) are also used in this study. Both sensors were also flown on the NASA ER-2 aircraft during TOGA COARE. The AMPR (Spencer et al. 1994) is a four-channel scanning microwave radiometer with frequencies at 10.7, 19.35, 37.1, and 85.5 GHz. Spatial resolution at nadir is about 2.8 km for 10.7 GHz and 0.6 km for 85.5 GHz when the aircraft flies at 20-km altitude. We use only the 10.7- and 85.5-GHz nadir view pixels in this study to determine liquid water path and dense ice scattering. MAS has 12 channels ranging from visible to infrared (King et al. 1996). Here we use the 12-μm channel radiance to calculate the equivalent blackbody temperature. The spatial resolution of MAS is about 50 m when the aircraft flies at an altitude of 20 km.

3. Ice water path algorithm

a. In situ measurements of ice microphysical parameters

In order to conduct the theoretical development of an ice water path algorithm, microphysical data from 29 CEPEX aircraft flights are studied to obtain mean properties of ice particles. The particle size is expressed by its diameter, $D$, which is defined as the ice particle’s longest dimension. A mass median diameter, $D_{mm}$, is used to characterize the mass distribution of the ice particle spectrum, whereby $D_{mm}$ is the diameter by which ice particles in the spectrum are divided into two groups with equal mass.

Figure 1 shows the average vertical distributions of
Fig. 1. The averaged vertical profiles of (a) ice water content and (b) mean mass median diameter and its standard deviation from 2DC measurements during CEPEX.

(a) ice water content and (b) mean mass median diameter and its standard deviation for all the available data from CEPEX. Data in the region colder than $-60^\circ$C are less representative because of smaller sampling number. On average, ice particles are smaller at colder temperatures. Larger ice water contents most frequently occur at warmer temperatures (lower altitudes), where ice particles are commonly observed as aggregates (McFarquhar and Heymsfield 1996). Ice particle size distributions are shown in Fig. 2 for every 10°C temperature interval averaged over all available data. In this figure, dots are observations and lines are the fitting curves of the following equation that is derived in this study:

$$N(D) = N_0 \left( \frac{100}{D} \right)^{3.5}, \quad D \leq 100 \, \mu m,$$

$$N(D) = N_0 \exp \left[ -5 \left( \frac{D - 100}{D_{mm} + 500} \right)^{0.75} \right], \quad D > 100 \, \mu m,$$

where $N(D)$ is the number concentration ($m^{-3} \, \mu m^{-1}$), $D$ is the diameter ($\mu m$), $N_0$ is a constant that corresponds to the ice concentration at 100 $\mu m$, and $D_{mm}$ is the mean mass median diameter as shown in Fig. 1 and can be fitted by the following equation as a function of air temperature ($t$):
\[ D_{\text{mun}} = 750 + 10t, \]  
(2)

where \( t \) is in degrees Celsius and \( D_{\text{mun}} \) is in micrometers. As shown in (1) and (2) the size distribution of the ice particles is temperature dependent. Note that the size distribution at the smaller end of the size spectrum (e.g., \( D < 100 \, \mu m \)) is less representative because of poor sampling efficiency of the 2D probe for small size particles at aircraft speed.

b. Algorithm development

To investigate the microwave scattering signals of tropical ice clouds, a plane-parallel radiative transfer model (Liu and Curry 1993) is utilized. In this model ice particles are assumed to be spheres with equivalent volume of the nonspherical ice particles. It is not clear how this approximation affects the model results because of the nonsphericity of ice particles. Evans and Stephens (1995a,b) studied the nonsphericity effect using a discrete dipole approximation for five ice particle shapes (solid columns, hollow columns, plates, rosettes, and spheres). They pointed out that the sensitivity of brightness temperature to ice water path could vary about a factor of 2 due to different shapes, with solid columns having the highest and rosettes having the lowest sensitivity in most of the particle size range. A more recent study by Evans et al. (1998) indicates that this uncertainty is even larger (as large as a factor of 3.6 at 220 GHz). However, since most cirrus contain a mixture of ice particles of several different shapes, the uncertainty range may be an overestimate. McFarquhar and Heymsfield (1996) pointed out that during CEPEX “most crystals observed with the 2DC were classified as having indeterminant shapes,” and “aggregates and suggestions of side planes were common when IWC [ice water content] was high (0.1 g m\(^{-3}\)).” In view of uncertainty of the habit and orientation of the ice particles in tropical ice clouds, we conclude that the most feasible method at this point to deal with this problem is to use the ice sphere approximation with equivalent volume. However, one must keep the potential effects of particle shape in mind when interpreting the model results.

Using the mean profiles of ice water content and size distribution shown in Figs. 1 and 2, the modeled sensitivity for selected SSM/I, SSM/T2, and MIR channels is calculated (Fig. 3). We analyzed the bulk density using the particle mass and diameter information given in the CEPEX dataset. A mean bulk density is then derived for every 5°C temperature interval. The bulk density is then used to calculate the diameter of equivalent-volume ice sphere. A calm ocean surface with temperature of 300 K is assumed in the calculation. A liquid water cloud having liquid water path of 400 g m\(^{-2}\) was assumed to be located below freezing level in a standard tropical atmosphere. The sensitivity is defined as \( (T_b - T_{m0})/IWP \), where IWP is the ice water path and equals 850 g m\(^{-2}\) for the profile shown in Fig. 1a; and \( T_b \) and \( T_{m0} \) are, respectively, brightness temperatures for conditions with and without the ice cloud. There is little sensitivity to channels lower than 85 GHz, the highest frequency of the SSM/I instrument, for this “mean tropical ice cloud.” The sensitivity is about 0.09 K (g m\(^{-2}\))\(^{-1}\) for 150 GHz and 0.12 K (g m\(^{-2}\))\(^{-1}\) for 220 GHz, significantly higher than those channels near 90 GHz. Therefore, 150- and 220-GHz channels are chosen for the IWP retrievals in this study. Note that these channels are still not sufficiently sensitive to thin cirrus cloud. Given the uncertainty in brightness temperature of about 1 K, it is impossible for 150 GHz to detect a cloud with an IWP less than 11 g m\(^{-2}\), which is equivalent to a 100-m-deep cirrus cloud with ice water content of 0.11 g m\(^{-3}\). In addition, ice particles in thin cirrus tend to have smaller sizes than the mean sizes shown in Fig. 1. This further reduces the ability for 150 GHz to detect thin cirrus because the scattering intensity is proportional to the sixth power of the particle diameter.

To evaluate how the high-frequency brightness temperatures change with different cloud conditions, we conducted 2353 radiative transfer model runs in which relative humidity varies over a range of 40%-100%, cloud (droplets size less than or equal to 100 \( \mu m \) in radius) liquid water path varies from 0 to 1200 g m\(^{-2}\), ice water path varies from 0 to 7700 g m\(^{-2}\), and rainfall rate varies from 0 to 50 mm h\(^{-1}\). Cloud liquid water and rain water are located below the freezing level, which is located at 5 km. The specified ice water content profiles have the same shape as shown in Fig. 1 while varying in magnitude. Figure 4 shows the scatterplot of brightness temperatures of 89 versus 220 GHz. The cases without ice are shown by open circles and those
with ice by crosses. The 220-GHz brightness temperature is saturated even if there is no ice in the cloud. For the nonice cases, there is little change in 220-GHz brightness temperature compared to about 70-K changes in 89-GHz brightness temperature due to variations in water vapor and liquid water. For the ice cases, the decrease in 220-GHz brightness temperature is much faster than that at 89 GHz. The pattern in 89 versus 150 GHz scatterplot (not shown) is similar to Fig. 4, except that for the nonice cases 150 GHz does not saturate until 89 GHz increases to about 240 K.

For the ice water path parameterization, we adopt a similar approach to that of Liu and Curry (1996) in which SSM/T2 channels were used. By examining the radiative transfer equation, they found that the following parameter $\beta$ is approximately proportional to the integral of volume scattering cross section of ice particles:

$$\beta = \frac{T_{B0} - T_B}{T_{B0} - T_{BA}},$$  \hspace{1cm} (3)

where $T_B$ and $T_{B0}$ are, respectively, the brightness temperatures (150 or 220 GHz in this study) under conditions with and without ice. Here, $T_{BA}$ is a constant to characterize the atmospheric radiation. A value of $T_{BA} = 240$ K is used in this study for tropical conditions, based upon model calculations. Since the scattering cross section of ice particles is related to the total ice amount (proportional to the sixth moment of the size distribution in Rayleigh regime), $\beta$ will be a indicator of the ice water path. The $\beta$–ice water path relation is also affected by the particle size distribution because liquid water path is proportional to the third moment, while $\beta$ is proportional to the sixth moment of the size distribution.

Similar to Liu and Curry (1996), $T_{B0}$ is determined by a scatterplot of brightness temperatures of 89 versus 220 GHz (or 150 GHz). Figure 5 shows the relative frequency of pixel occurrence in the 89 versus 220 GHz brightness temperature diagram observed by MIR for all the aircraft flights during TOGA COARE. These data include only nadir views when the aircraft flew above 18 km and have both pitch and roll smaller than 5°. The pattern of the diagram is very similar to that simulated by the radiative transfer model (Fig. 4). A large number of data points are located at the top of the diagram, where the model indicates the presence of no or few ice particles. In Liu and Curry’s (1996) study for the North Atlantic during winter, the SSM/T2 92-GHz channel was seldom saturated due to the low water vapor amount, and $T_{B0}$ at 150 GHz was determined by the 92-GHz brightness temperature for the entire range of ice water path. However, in the Tropics, the 89-GHz brightness temperature easily reaches its maximum, as shown in Figs. 4 and 5. For applications to the Tropics, we determine $T_{B0}$ using the Liu and Curry method only for low ice amount conditions. We assign the “low ice conditions” when the 220-GHz (or 150 GHz) brightness temperature is higher than 250 K. Although this definition seems somewhat arbitrary, it is seen from Fig. 5 that the 89-GHz brightness temperature has not started to sharply decrease within this range. In the low ice amount range, $T_{B0}$ is found using the scatterplot of 89 versus 220 (or 150 GHz), as described by Liu and Curry (1996). For higher ice amount conditions, 89 GHz is no longer useful for the $T_{B0}$ determination because it starts to decrease, and we simply use a constant value of $T_{B0}$. The constant is 280 K for 150 GHz and 275 K for 220 GHz. Note that the value 275 K is approximately the modeled 220-GHz brightness temperature in Fig. 4 when the 89-GHz brightness temperature starts to decrease.

Using the results from the 2353 model runs described above, the relationship between $\beta$ and IWP is established. Figure 6 shows the relationship between $\beta$ and IWP when using 150- and 220-GHz channels. The best-fit curves can be expressed by

$$\text{IWP} = \sum_{n=1}^{5} c_n \beta^n,$$  \hspace{1cm} (4)

and the coefficients, $c_n$ ($n = 1, \ldots, 5$), are listed in Table 1.

It should be mentioned that (4) is developed purely from the radiative transfer model results, which partially use CEPEX microphysical data as input. Errors in this equation may arise from the incomplete representation of the actual tropical clouds by the model inputs and inaccurate treatment of ice scattering by the model. Obviously, these errors are difficult to quantify. From Fig. 6, it is seen that the parameter $\beta$
starts to decrease its sensitivity dramatically when IWP exceeds 4000 g m$^{-2}$ for 150 GHz and 2000 g m$^{-2}$ for 220 GHz. Therefore, the error for large values of IWP could be larger because of the sensor’s insensitivity.

For the purpose of comparing retrievals from the two channels, we created a subset of nadir MIR data in which the aircraft flew above 18 km and had both pitch and roll angles less than 3°. Values of IWP from the 150- and 220-GHz channels are calculated for this subset using (4) and are plotted in Fig. 7. The total number of IWP pairs is 84,358 with IWP ranging from 0 to more than 5000 g m$^{-2}$. IWPs from the two channels are closely correlated with a correlation coefficient of 0.96. Their means are both around 200 g m$^{-2}$. Discrepancies between the two retrievals increase with increasing IWP. Although the discrepancies could be caused by a number of factors, we anticipate that the 220-GHz retrievals are less reliable than 150-GHz retrievals for high values of IWP because the 220-GHz channel saturates at those IWPs and then becomes insensitive to IWP variations.

Theoretically, the 220-GHz channel has greater skill for the thinner ice clouds (lower IWPs) and the 150-GHz channel has greater skill for thicker ice clouds (higher IWPs). To take the advantage of both channels, we use the following combination as the final IWP algorithm:

\[
\begin{align*}
\text{IWP}_{220} & \quad I \leq 100 \text{ g m}^{-2}, \\
\text{IWP} & = a \times \text{IWP}_{150} + (1 - a) \times \text{IWP}_{220}, \quad 100 < I < 1000 \text{ g m}^{-2}, \\
\text{IWP}_{150} & \quad I \geq 1000 \text{ g m}^{-2},
\end{align*}
\]
FIG. 6. Simulated relationships between $\beta$ and ice water path (IWP) for 150 and 220 GHz. The fitting curves (4) are also shown in the figure.

TABLE 1. Coefficients in Eq. (4).

<table>
<thead>
<tr>
<th>Channel</th>
<th>$c_1$</th>
<th>$c_2$</th>
<th>$c_3$</th>
<th>$c_4$</th>
<th>$c_5$</th>
</tr>
</thead>
<tbody>
<tr>
<td>150 GHz</td>
<td>580.762</td>
<td>-459.664</td>
<td>456.826</td>
<td>-168.112</td>
<td>22.9881</td>
</tr>
<tr>
<td>220 GHz</td>
<td>548.912</td>
<td>-750.292</td>
<td>566.069</td>
<td>-167.092</td>
<td>17.7469</td>
</tr>
</tbody>
</table>

where $a = (1/9)(I/100 - 1)$, $I = (1/2)(IWP_{220} + IWP_{150})$, and $IWP_{150}$ and $IWP_{220}$ are IWP retrievals from 150 and 220 GHz, respectively. That is, the 220-GHz retrievals are used for IWP lower than 100 g m$^{-2}$, and a linear combination is used for IWP in between.

c. Effects of particle size and supercooled cloud water

One of the major uncertainties in the algorithm described above is the use of mean mass median particle diameter in determining size distribution. As shown in Fig. 1b, the mean mass median diameter varies over a wide range from case to case, and the standard deviation is about 50% of the mean mass median diameter value. Evans and Stephens (1995b) pointed out that particle size has a large effect on the brightness temperature sensitivity to ice water path variation.

Because its standard deviation is about 50% of the value of mean mass median diameter, we conduct two additional sets of radiative transfer model runs using the same databases as described in section 3b except that the mass median diameters are, respectively, 50% smaller and 50% larger than those given by (2). Similar to Fig. 6, Fig. 8 shows the simulated relationship between $\beta$ and IWP for mass median diameter being the same as (2) (o), 50% smaller (x), and 50% larger (+). The different mass median diameters cause a wider spread of $\beta$ for a given value of IWP, especially for 150 GHz. For a given IWP, a larger particle size tends to result in a bigger $\beta$ or overestimation of IWP by the algorithm. From (4) the uncertainty of IWP due to changes in $\beta$ can be written as

$$\Delta IWP \approx \left( \sum_{n=1}^{5} nc_n \beta^{n-1} \right) \Delta \beta.$$  (6)

Using the $\beta$ difference ($\Delta \beta$) between model simulated and calculated by (4), the possible error ($\Delta IWP$) is calculated and shown in Fig. 9. Note that the uncertainties shown in Fig. 9 include those due to particle size variations as well as those due to changes in water vapor, cloud liquid water, and precipitation because the latter effects were included in the original 2353 model simulations. The variation in particle size indeed is a big contributor to the estimation error, especially for 150-GHz channel and the higher values of IWP. According to these calculation results, the error could be as high as plus or minus 50% of the IWP values in some cases. Therefore, it is believed that the particle size effect is the biggest uncertainty in the current retrieval algorithm. Deeter (1997) proposed an algorithm to retrieve ice water path and particle size simultaneously, which could minimize the error caused by the uncertainty in particle size.

Another uncertainty may arise from the existence of supercooled cloud water in the ice cloud layer. This uncertainty depends upon both the amount of supercooled liquid water and its relative location to the ice cloud. To investigate this uncertainty, we conduct four
sets of radiative transfer model runs with 200 g m\(^{-2}\) liquid water below freezing level (warmer than 0°C) and ice water path changing from 0 to about 1800 g m\(^{-2}\) in all of them. The first set contains no supercooled liquid water. The second, third, and fourth sets contain 100 g m\(^{-2}\) liquid water at mean temperatures of \(-3^\circ\), \(-10^\circ\), and \(-16^\circ\)C, respectively. The results are shown in Fig. 10. Figures 10a,b show the LWP–β scatterplots and the curve of Eq. (4), and Figs. 10c,d show the error caused by the inclusion of the supercooled liquid water as calculated by (6). For none or very thin ice layer, supercooled liquid water tends to lower the brightness temperature and cause overestimation of ice water path. However, as ice water path is greater than about 200 g m\(^{-2}\), it causes underestimation of ice water path. Supercooled liquid water at higher altitudes causes greater underestimation. Note that a 100 g m\(^{-2}\) of supercooled liquid water at \(-16^\circ\)C is very large relative to what could occur in natural ice clouds. Therefore, the real error caused by supercooled liquid water is likely smaller than what is shown in Fig. 10. A rough estimation of this underestimation based on the above calculations is about 30%. To study the supercooled liquid water effect in a more precise manner, further observations are needed of both supercooled water and ice water contents and their relative location. Minimizing this uncertainty remains a challenge in future algorithm development for ice water remote sensing.

d. Algorithm validation

Evaluation of the retrieval algorithm is done by comparing the IWP\(\text{s}\) retrieved from MIR data with IWP\(\text{s}\) measured in situ by a 2D-Grey probe flown on a DC-8 aircraft. During TOGA COARE, 12 coordinated flights were conducted between the ER-2 and DC-8, with the ER-2 flying over the cloud top and the DC-8 inside the cloud. During these flights the two aircraft flew over the same area at almost the same time. Although these data seem to be ideal for the algorithm validation, the following uncertainty must be kept in mind. MIR-retrieved IWP is a vertically integrated quality that should be compared with the same quality derived from a sampled vertical IWC profile. However, there was no vertical IWC profile taken by the DC-8 within a short horizontal distance during the TOGA COARE missions. Most of the vertical profiles typically covered a horizontal distance of 50–300 km when the DC-8 aircraft was making a slant or spiral ascent/descent. Within this distance the aircraft may pass several different IWP regimes. Therefore, it is impossible to compare the IWP from the 2D probe with the MIR IWP.
Fig. 8. Radiative transfer model simulated relationship between $\beta$ and ice water path for 150 and 220 GHz. Three sets of mass median diameters are used: the same as (2) (o), 50% larger (+), and 50% smaller (×).

Fig. 9. Estimated errors by (6). Three sets of mass median diameters are used: the same as (2) (o), 50% larger (+), and 50% smaller (×).

derived at any single location. Instead, we compare the 2D IWP with the average MIR IWP over the area where 2D sampling was done, which usually comprised an area of several tens of kilometers on a side. For this reason we must interpret the comparison results with caution.

From the TOGA COARE dataset, seven cases were used to make the comparison (Fig. 11). In Fig. 11 the aircraft IWC profiles and IWPs ($IWP_A$) are derived from 2D measurements, and the average MIR-retrieved IWPs ($IWP_E$) and the IWP frequency distribution are calculated from (5) using data covering the entire area where the IWC profile was made. A scatterplot of $IWP_E$ versus $IWP_A$ for the seven cases is shown in Fig. 12. The error bars indicate the standard deviation ($\sigma$) of MIR IWPs within the area where averaging was made. Table 2 lists some of the characteristics of each case, which are based on McGaughey and Zipser (1995). In case (e), the 2D probe measured 7 g m$^{-2}$ ice water and the MIR retrieval is 1 g m$^{-2}$ with $\sigma = 7$ g m$^{-2}$. In case (c), the 2D IWP is 3 g m$^{-2}$ and the MIR IWP is 28 g m$^{-2}$ with $\sigma = 49$ g m$^{-2}$. These discrepancies may indicate the algorithm’s thresholding ability for discriminating ice and no-ice clouds. Cases (b), (f), and (g) show good agreement between 2D $IWP_A$ and MIR $IWP_E$, which include both convective clouds and thick cirrus clouds. The largest discrepancy occurs for case (d) in which the MIR IWP is only about half of the 2D IWP. This case is for Trop-
Fig. 10. Radiative transfer model simulated relationship [(a) and (b)] and estimated error [(c) and (d)] when including supercooled cloud liquid water. (a) and (c): For 150 GHz; (b) and (d): for 220 GHz.

Figure 10 illustrates the simulated relationship and estimated error for the radiative transfer model when supercooled cloud liquid water is included. The simulations were conducted for 150 GHz [(a) and (c)] and 220 GHz [(b) and (d)].

Cyclone Oliver, in which the DC-8 sampled the eyewall region from about 1910 to 2030 UTC 8 February 1993, while the ER-2 surveyed a larger area including the eyewall and outer clouds. Because of the high variability of IWPs near the eyewall, the comparison of the averaged value could be very questionable. Another possible explanation of the discrepancy in this case could be the saturation of the microwave channels for high ice concentrations, which causes underestimation.

The comparisons in Figs. 11 and 12 show that the retrieved IWPs and in situ measured IWPs appear to agree reasonably well with each other except for case (d). Because of the small number of cases and problems with the validation data, it is inappropriate to assess the absolute accuracy of the algorithm based on these limited comparisons. In particular, it is unclear how the 2D IWC profiles obtained by a few (usually one or two) ascent/descents across several tens of kilometers are representative of the average vertical profile over that region. Another issue that should be noted here is the difference between CEPEX cases, which are used to construct our algorithm, and the TOGA COARE validation cases. While CEPEX cases are mainly cirrus anvils, the TOGA COARE cases include data from convective cores. This difference may also cause the scatter in Fig. 12, particularly for case (d). Further validation by using more adequate “truth” in future field experiments is highly desirable.

4. Case studies

Two case studies are shown in this section. The first one is intended to show ice water in deep convective cells for a matured tropical cyclone, Oliver, on 7 February 1993 (Fig. 13). This case was also discussed by Spencer et al. (1994) and Schwartz et al. (1996). In Fig. 14 a 4-h time series of retrieved ice water path retrieved from MIR, AMPR 10.7-GHz (TB10) and 85.5-GHz (TB85) brightness temperatures, and MAS 12-μm equivalent blackbody temperature (IR TB) are shown. The 10.7-GHz brightness temperature is an indicator of total liquid water (both cloud and rainwater) in the vertical column because it is rarely affected by ice scattering (Smith et al. 1994). The 85.5-GHz reflects the amount of “dense ice particles,” such as graupel, etc. The ER-2 flew over the cyclone’s main cloud system twice at around 1700 UTC (from west to east) and 2000
Fig. 11. Comparison between retrieved (IWP_e) and in situ measured (IWP_s) values of ice water path for seven TOGA COARE cases. Each figure consists of an ice water content profile and an ice water path frequency distribution. The ice water content profiles are generated from in situ data and the ice water path frequency distributions are from MIR retrievals.
Fig. 12. Scatterplot of MIR retrieved vs 2D-Grey in situ measured ice water path for the seven cases in Fig. 11. The error bars indicate the standard deviation of IWPs within the area where IWP averaging is made.

UTC (from east to west). The eye and eyewall of this cyclone are clearly shown of all these channels. During the time between the two cyclone overpasses, the ER-2 sampled the convection to the east of the cyclone. Two things are notable from this figure. First, all cells with ice water path greater than 1500 g m\(^{-2}\) also have high liquid water amount (peaks in TB10) and high amounts of dense ice (dips in TB85). These signatures represent well-developed cloud/rain cells with large amounts of liquid water below the freezing level and ice water above. Second, some cells (marked by small circles in the TB10 panel) only have high liquid water amount (high TB10) but are not recognizable in either the MIR ice or 85.5-GHz dense ice signatures. It is expected that these are young convective cells that have not yet formed significant amounts of cloud ice.

The second case is thick cirrus clouds associated with convective cells on 1 February 1993 (Fig. 15). Similar to Fig. 14, the retrieved ice water path, AMPR 10.7- and 85.5-GHz brightness temperature and MAS 12-\(\mu\)m equivalent blackbody temperature are shown in Fig. 16, except for a logarithmic scale being used for ice water path in order to show the low values. During this time period the aircraft passed over an island twice (indicated in TB10 panel). The two AMPR microwave channels responded to the “warm” land surface clearly, while the MIR ice water path retrievals seem to be unaffected because the high water vapor concentration masked the radiation from the surface. There is only one deep convective cell encountered during this time period around 0100 UTC, which is characterized by high ice water path, high TB10, and low TB85. Around 0045 UTC there is another cell having an ice water path greater than 500 g m\(^{-2}\), but only a very weak response is shown in the TB10, and the TB85 shows a small increase, indicating that the cloud contains a small amount of liquid water and basically no dense ice. Ice water path, ranging from 0 to about 500 g m\(^{-2}\), is seen during the rest of the time period, while the TB10 did not show a clear liquid water signal nor did the TB85 show a dense ice signal.

In the above two cases, the incoherent variation of the signals from different channels illustrates the complexity of the microphysical composition of the tropical clouds. Therefore, it is expected that a multichannel approach would be a better way to understand the cloud properties.

5. Ice water path characteristics in tropical clouds during TOGA COARE

In the following subsections, we compare retrieved IWPs with cloud top temperature (from MAS) and liquid-water/rain information (from AMPR). This multichannel approach requires data from three different sensors, that is, AMPR, MIR, and MAS. To collocate data from the different sensors, only nadir observations are used, and the following number of original pixels in every scanline were averaged so that a new pixel size is created to make comparable observations from the different channels: 2 for AMPR 10.7 GHz, 5 for all MIR channels, and 70 for the 12-\(\mu\)m MAS channel. In addition, data are averaged over 18 s to represent an area of approximately 3.5 km \(\times\) 3.5 km. The total number of new pixels generated in this way from all 12 flights is 6969.
Fig. 13. GMS imagery at 1834 UTC 7 February 1993 showing the clouds and ER-2 flight track.

Fig. 14. Time series of MAS 12-μm equivalent blackbody temperature (IR TB), AMPR 85.5-GHz (TB85), and 10.7-GHz (TB10) brightness temperatures, and MIR retrieved ice water path for the 7 February 1993 flight.
a. Cloud classification

It is expected that clouds formed by different physical processes could have different ice water path characteristics. To account for this difference we adopted a cloud classification scheme similar to the one developed by Liu et al. (1995), in which they used Geostationary Meteorological Satellite infrared and SSM/I microwave data. MAS IR and AMPR microwave data will be used in this study. The cloud classification scheme is shown in Fig. 17, and the following cloud classes are defined: wnp, warm nonprecipitating cloud; wp, warm precipitating cloud; mnp, mid nonprecipitating cloud; mp, mid precipitating cloud; hnp, high nonprecipitating cloud; hlp, high light precipitating cloud; and dhp, deep heavy precipitating cloud. The shading in the figure indicates the frequency distribution of data occurrence. The boundaries between warm and mid clouds and between mid and high cloud are IR temperatures 0° and −40°C, the same as those used by Liu et al. (1995). Because there is no depolarization information in AMPR channels, the 10.7-GHz brightness temperature is used to replace Liu et al.’s microwave index. The 10.7-GHz channel is used because it is the least affected by ice particles and therefore provides independent information from that in MIR channels. A relationship between the 10.7-GHz brightness temperature and rainfall rate (Fig. 18) is generated using the radiative transfer model and the results of the above-mentioned 2353 model runs. Based on Fig. 18, the 10.7-GHz brightness temperature of 137 K is selected as the rain threshold. The boundary of high light and deep heavy precipitating clouds is determined by a 10.7-GHz brightness temperature of 193 K, which corresponds to a rainfall rate of 10 mm h⁻¹. Because deep convection usually produces heavier rainfall than stratiform clouds, the heavy precipitating clouds are more likely to be deep convection and the light precipitating clouds are more representative of stratiform rain clouds.

b. Ice water path frequency distributions

The IWP frequency distributions in each 50 g m⁻² bin are shown in Fig. 19 for each of the seven cloud classes. The total pixel number and average IWP of each cloud class are also shown in the figure. There are about 1519 pixels (21.8% of the total) in the warm nonprecipitating class and the average IWP is virtually zero. This assures that the algorithm’s threshold works reasonably for this cloud category. For the warm precipitating class the average IWP is 14 g m⁻² and there are 3 pixels in the 50–100 g m⁻² bin and 1 pixel in the 100–150 g m⁻² bin. There are possibly several reasons for the nonzero IWP. However, the problem is most likely associated with the ice threshold. Because this
algorithm does not produce negative IWP (zero IWP values are assigned for all negative $\beta$s), the uncertainty in threshold could only result in a positive averaged IWP. The magnitude of the positive IWP is small compared with the IWP's in the "cold" cloud categories, and the IWP spectra in mid and high/deep clouds are significantly wider than those in warm clouds.

Generally speaking, the precipitating clouds have larger IWP values than nonprecipitating clouds, and clouds with colder tops tend to have larger IWP values. The average IWP for high nonprecipitating clouds is about six times larger than the average IWP for mid nonprecipitating clouds. For the precipitating clouds, the IWP in high light precipitating cloud is also about six times of that in mid precipitating clouds. The maximum frequency in the IWP distributions is near 0 for all cloud classes except for the deep heavy precipitating cloud, which has a wide mode ranging from 500 to 2000 g m$^{-2}$. IWP in deep heavy precipitating cloud can be more than 5000 g m$^{-2}$. Roughly speaking, the maximum IWP's are 500 g m$^{-2}$ for mid nonprecipitating cloud, 1000 g m$^{-2}$ for mid precipitating and high nonprecipitating clouds, and 3000 g m$^{-2}$ for high light precipitating cloud.

c. Relationships between ice water path, cloud-top temperature, and liquid water amount

For cloud climatology and cloud physics studies, it is useful to know how the liquid water, ice water, and cloud-top temperature are related in tropical clouds. In this subsection we examine these relations using the TOGA COARE MIR, AMPR, and MAS data. Let us first examine the relationship between IWP and TB10 (which is a proxy for total liquid water path and/or rainfall rate). Figure 20 shows the IWP averaged in every 2-K TB10 bin. (If the pixel number in a bin is less than 3, the averaging was not done and no dot is shown for that bin.) It is seen that high/deep cloud liquid and ice water amounts are positively correlated, implying that on average clouds having more liquid water also tend to have more ice water. This tendency seems to be more evident for high nonprecipitating and high light precipitating clouds, for which there are more data pixels and therefore the relationship is more meaningful. There seems to be no clear relationship between liquid and ice water for mid clouds. If any, it may be the reverse relation for mid nonprecipitating cloud. Although the physics behind this result is not clear, it seems that liquid and ice water in clouds with a top temperature warmer than $-40^\circ$C are either decoupled or inversely correlated. There is also the possibility that supercooled cloud water in the warmer clouds plays a role in determining the relationship between IWP and TB10. As shown in Fig. 10, because of its colder temperature than clouds below freezing level, supercooled cloud water could lower the brightness temperature and lead the algorithm to overestimate IWP when there are no or few ice particles in the cloud. But if there are sufficient ice particles in the cloud and the supercooled cloud water is located above them, the supercooled water could raise the brightness temperature and cause underestimation of IWP. The net effect of having supercooled water in the cloud, therefore, will depend on both supercooled water and ice water content as well as their relative locations.

The averaged IWP in each 2°C MAS IR TB bin is shown in Fig. 21 for non-, light, and heavy precipitating clouds, with a logarithmic scale used for IWP. An increase of IWP with the decrease of cloud-top temperature can be seen for all cloud types, while nonprecipitating clouds have lower IWP than the precipitating clouds for a given cloud-top temperature. On a logarithmic scale, IWP is almost linearly related to cloud-top temperature except for clouds with top temperature warmer than $-20^\circ$C. It is also seen that the relationship for mid precipitating cloud is noisier than those for other cloud types. Recalling that the relationship between IWP and liquid water path for mid precipitating cloud is also unclear (Fig. 20), it is expected that the microphysical process in a mid precipitating cloud is likely more complex than the other cloud types. A similar plot for the relationship between cloud-top temperature and
FIG. 17. Cloud classification based on AMPR 10.7-GHz and MAS 12-μm brightness temperatures. The shading indicates the frequency of occurrence in the TOGA COARE observations. See text for details.

FIG. 18. Modeled relationship between rainfall rate and 10.7-GHz brightness temperature. The 10.7-GHz brightness temperature is shown in Fig. 22. Comparing Figs. 21 and 22 it is clear that the ice water path is much more closely related to cloud-top temperature (or cloud-top height). Except for heavy precipitating clouds with cloud-top temperatures lower than −60°C, cloud-top temperature shows little skill in representing total liquid water path or rainfall rate.

Finally, it should be mentioned that the relations derived in this subsection are averages for all of the data. Therefore, they are meaningful only in a statistical sense. To illustrate the deviation of the relationship for individual pixels from the average we show the scatterplot of IWP versus TB10 in Fig. 23, for which the averaged relationship is shown in Fig. 20. Although there is still significant correlation between IWP and TB10 for the high/deep clouds (correlation coefficient equals 0.5), the scatter is also considerable.

6. Conclusions

An ice water path (IWP) retrieval algorithm using airborne MIR 89-, 150-, and 220-GHz brightness temperatures was developed for tropical ice clouds. Using this algorithm, characteristics of IWP during TOGA
COARE were investigated, emphasizing the relationships among ice water, cloud-top temperature, and column liquid water (including cloud and rain water). The algorithm is based on the results from a large number of radiative transfer simulations. To conduct these simulations, vertical distributions of ice particle properties collected from in situ aircraft measurements during CECPEX were first analyzed and characterized. These properties were then utilized to construct the radiative transfer model inputs. The IWP algorithm first calculates retrievals using both the 150- and 220-GHz channels.

Fig. 19. Frequency distributions of ice water path for the seven classes of clouds. Total pixel number and averaged ice water path for each class are also shown.

Fig. 20. Averaged ice water path in every 2-K TB10 bin for mid (upper panel) and high/deep (bottom panel) clouds. TB10 is the brightness temperature at AMPR 10.7 GHz.

Fig. 21. Averaged ice water path in every 2°C bin of IR TB for non-, light, and heavy precipitating clouds. Here, IR TB is MAS 12-μm equivalent blackbody temperature.
Based on the consideration that the 150-GHz channel is more sensitive to higher IWP and the 220-GHz channel is more sensitive to lower IWP, the final retrieval combines the 150- and 220-GHz retrievals. Validation of the IWP retrieval algorithm was conducted by comparing remote-sensed IWP to in situ measured IWP for aircraft data collected during TOGA COARE. The results show reasonable agreement between the retrieved and in situ IWPs. Because of the small number of validation cases and the quality of the validation data, it is difficult to assess the algorithm’s absolute accuracy. More comparisons with in situ observations need to be done in the future.

Using brightness temperatures at AMPR 10.7-GHz and MAS 12-µm to represent liquid water/rainfall and cloud-top temperature signatures, the observed clouds are categorized into seven different classes: warm nonprecipitating, warm precipitating, mid nonprecipitating, mid precipitating, high nonprecipitating, high light precipitating, and deep heavy precipitating clouds. The average IWP and IWP frequency distribution of each of the seven classes are studied. The results show that clouds with higher tops have greater IWP and wider IWP spectra, and precipitating clouds have greater IWP and wider IWP spectra than nonprecipitating clouds given the same cloud-top temperature. IWP in deep heavy precipitating clouds can be more than 5000 g m\(^{-2}\), though its peak frequency occurs around 1000 g m\(^{-2}\). Roughly speaking, the maximum IWPs are 500 g m\(^{-2}\) for mid nonprecipitating cloud, 1000 g m\(^{-2}\) for mid precipitating and high nonprecipitating clouds, and 3000 g m\(^{-2}\) for high light precipitating cloud. On average, ice water path is positively correlated to column liquid water except for mid clouds and negatively correlated to cloud-top temperature. In particular, ice water path increases exponentially with the decrease in infrared brightness temperature except for clouds with top temperature warmer than \(-20^\circ\text{C}\). It is also shown that ice water path is much more closely related to cloud-top temperature than is liquid water path or rainfall.

Although further validation and improvement of the ice water path retrieval algorithm are needed in the future, this study shows encouraging results of using MIR data to retrieve ice water in tropical clouds. As MIR will also be flown on aircraft in future field experiments, this study provides guidance in the application of retrieving ice water properties from MIR data. Moreover, since similar frequencies are used in currently operating satellites, for example, DMSP SSM/T2 and NOAA AMSU-B, the analyses in this study may also be helpful for developing satellite algorithms using high-frequency microwave data.

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