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Key Points:

- It shows a simple cloud retrieval uncertainty quantification method
- It shows different uncertainty contributions from various influential factors
- It shows different retrieval uncertainties among various types of clouds

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Quantifying uncertainties of cloud microphysical property retrievals with a perturbation method

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Abstract Quantifying the uncertainty of cloud retrievals is an emerging topic important for both cloud process studies and modeling studies. This paper presents a general approach to estimate uncertainties in ground-based retrievals of cloud properties. This approach, called the perturbation method, quantifies the cloud retrieval uncertainties by perturbing the cloud retrieval influential factors (like inputs and parameters) within their error ranges. The error ranges for the cloud retrieval inputs and parameters are determined by either instrument limitations or comparisons against aircraft observations. With the knowledge from observations and the retrieval algorithms, the perturbation method can provide an estimate of the cloud retrieval uncertainties, regardless of the complexity (like nonlinearity) of the retrieval algorithm. The relative contribution to the uncertainties of retrieved cloud properties from the inputs, assumptions, and parameterizations can also be assessed with this perturbation method. As an example, we apply this approach to the Atmospheric Radiation Measurement Program baseline retrieval, MICROBASE. Only nonprecipitating single-phase (liquid or ice) clouds have been examined in this study. Results reveal that different influential factors play the dominant contributing role to the uncertainties of different cloud properties. To reduce uncertainties in cloud retrievals, future efforts should be emphasized on the major contributing factors for considered cloud properties. This study also shows high sensitivity of cloud retrieval uncertainties to different cloud types, with the largest uncertainties for deep convective clouds. Limitations and further efforts for this uncertainty quantification method are discussed.

1. Introduction

Clouds play a significant role in the climate system due to their modification effects on global radiation balance and atmospheric water cycle. However, representation of clouds in climate models remains one of the largest uncertainties for climate predictions [Intergovernmental Panel on Climate Change, 2007]. Therefore, accurate cloud observations are essential and urgently demanded.

The cloud properties can be obtained from various observations including in situ, space-borne, and ground-based observations. In situ aircraft observations are often used in evaluation of ground- and space-based observations and cloud process studies due to their direct measurements and high temporal resolution. However, these measurements have limitations due to their small sample volume and large financial cost. Moreover, in situ aircraft data are not always high quality. For example, shattering of ice crystals on probe tips makes in situ sampling of small ice crystals problematic. Even in today's instruments, there appears to be evidence of shattering though it does not seem to be as problematic as in times past. Satellite observations, with broad coverage area and coarse time resolution, are often used in climate model evaluation and cloud property statistical studies. Ground-based cloud observations, while covering a fixed site, can provide high time resolution and long-term continuous data, which are generally used in the evaluation of satellite observations, the study of cloud processes, and evaluation of model simulations. This study will focus on estimates of cloud microphysical properties from ground-based measurements by the Atmospheric Radiation Measurement (ARM) facility, whose primary goal is to carry out long-term observations of clouds and radiation for the purpose of improving their treatments in global climate models [Ackerman and Stokes, 2003].

The major cloud microphysical properties estimated from ARM measurements are cloud liquid water content (LWC), cloud droplet effective radius (r_{ei}), cloud ice water content (IWC), and cloud ice particle effective radius (r_{ei}). Various retrieval algorithms are available to obtain these cloud properties from the ARM ground-based

remote sensors (see technical report by *Zhao et al.* [2011]). For example, cloud LWC can be derived based on liquid water path (LWP) from a microwave radiometer (MWR) and radar reflectivity [*Frisch et al.*, 1995; *Dong and Mace*, 2001], or spectral infrared radiation [*Turner*, 2005; *Garrett and Zhao*, 2013]; cloud IWC can be obtained from radar reflectivity [*Liu and Illingworth*, 2000; *Shupe et al.*, 2005; *Hogan et al.*, 2006], or surface flux measurements and radar reflectivity [*Mace et al.*, 1998; *Turner et al.*, 2007], or radar reflectivity and Doppler velocity [*Mace et al.*, 2002; *Deng and Mace*, 2008], or radar reflectivity and lidar extinction coefficient [*Wang and Sassen*, 2002].

There are large differences among the various cloud products [*Comstock et al.*, 2007; *Turner et al.*, 2007; *Zhao et al.*, 2012; *Huang et al.*, 2012]. *Zhao et al.* [2012] have shown that differences among these cloud products can be explained by their differences in retrieval theoretical basis, assumptions, parameters, inputs, and constraints. It is necessary for us to understand and estimate the cloud retrieval uncertainties associated with these influential factors so that they can help cloud-related studies including better constraints for climate models.

Several methods can be used to quantify the cloud retrieval uncertainties, including the perturbation method, radiation closure testing, comparison with in situ observations, and observation system simulation experiments (OSSE) as proposed by the ARM focus group "Quantification of Uncertainty In Cloud Retrievals" (proposal whitepaper by *Xie et al.* [2011]). Each method has its advantages and limitations. For example, the radiation closure test can identify the retrievals that best match the observed surface and top-of-atmosphere radiation. However, different vertical combinations (profiles) of cloud properties could generate similar radiation properties at the surface or top-of-atmosphere. Comparing the retrievals with in situ measurements can only give information on cloud retrieval uncertainties for very limited periods and should be less reliable for other periods because of sample volume differences. Although OSSE is a good method to quantify the uncertainty caused by the cloud retrieval algorithm itself [*McFarlane et al.*, 2002; *Hogan et al.*, 2006], there are unknown uncertainties in the design of forward models in OSSE. The perturbation method roughly quantifies the cloud retrieval uncertainties by perturbing key parameters and/or changing key assumptions used in these selected retrieval methods, while limitations, as will be discussed in this paper, exist.

In general, there are two kinds of errors for any kind of retrievals, one is the bias error and the other random error. Bias error is a systematic inaccuracy caused by a mechanism that we can (ideally) control. We can adjust the retrievals (like regression equations) to account for bias errors. Random error is a nonrepeatable inaccuracy caused by an unknown or uncontrollable influence. Random errors establish the limits on the precision of a measurement. The regression equations used in a retrieval algorithm are usually obtained based on in situ aircraft measurements. However, without many in situ observation measurements, it is almost impossible to know the bias errors. In this study, we do not intend to quantify the bias errors, but simply quantify the retrieval random errors by using the perturbation uncertainty quantification method. We use the ARM baseline retrieval of cloud microphysical properties (MICROBASE [*Dunn et al.*, 2011]) to illustrate this method.

In this paper, section 2 introduces the perturbation method for cloud retrieval uncertainty analysis. Section 3 describes the MICROBASE cloud retrieval algorithm with the errors in inputs, assumptions, and parameters of empirical regression equations. Section 4 shows the results of cloud retrieval uncertainties. A discussion about the cloud retrieval uncertainties is presented in section 5.

2. A Perturbation Method for Uncertainty Analysis

As indicated by *Leith* [1974] for a forecast model, adding small perturbations to the analysis of the same magnitude as the analysis errors, and rerunning the model from the new initial condition, the effect of the initial errors can be estimated. For a cloud retrieval model, random perturbation errors can be added to the instrument inputs, empirical parameters, and assumptions that can be quantified. These perturbations should vary within the error ranges of the corresponding influential factors to which they are added. The retrieval errors can then be estimated from these cloud retrieval model runs. We call this the perturbation method in this paper. Considering that many cloud retrieval algorithms often use nonlinear regression relationships or forward models and that the retrievals often depend on multiple individual measurements, the uncertainties are impossible to ascertain with an analytical method, and this perturbation method provides an easy way for quantifying cloud retrieval uncertainties.

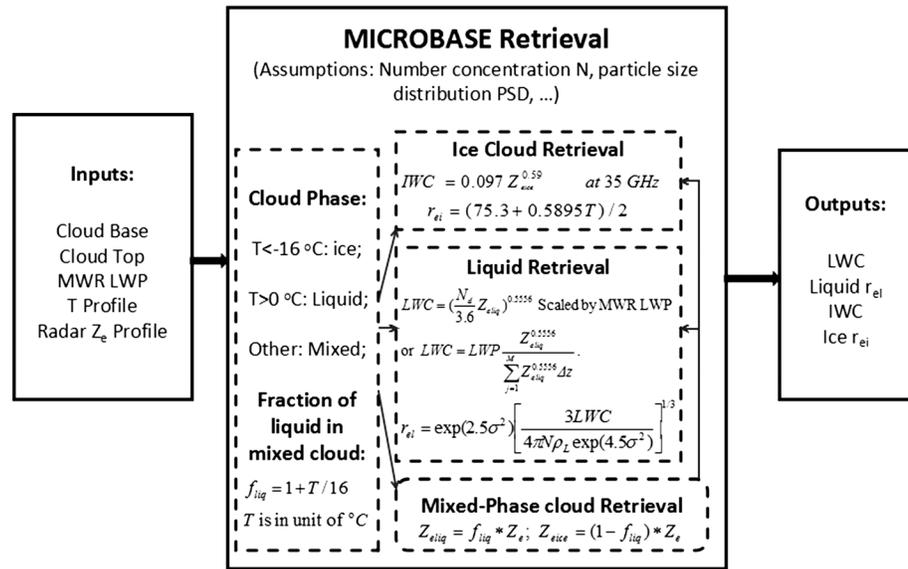


Figure 1. The diagram of cloud retrieval process in MICROBASE. The left column is the cloud retrieval inputs. The middle column is the retrieval algorithms, particularly the regression equations used to derive various cloud microphysical properties. The right column is the outputs of cloud microphysical properties. The liquid fraction in mixed-phase clouds is denoted by f_{liq} ; Z_{eliq} and Z_{eice} are equivalent radar reflectivity contributed from liquid and ice, respectively; other symbols have been explained in the text.

This cloud retrieval uncertainty perturbation analysis is similar to but much simpler than Monte Carlo simulations, which have been shown to successfully return the solutions that incorporate adjustments to assumptions on errors in observations and forward models. For example, *Posselt et al.* [2008] used Markov Chain Monte Carlo (MCMC) simulations to diagnose the characteristics of ice cloud property retrievals obtained from spectral radiation measurements.

Different from the full implementation of MCMC, the perturbation method here is a simplified application of MCMC. It borrows the idea of “perturbation” and considers the information from prior knowledge and forward model probabilistically, but does not include much information from observations except that some in situ observation-based statistical results are used in the perturbation process. The perturbation method is described as the following. For a given set of cloud retrieval inputs, we perturb every influential factor of the regression parameters, assumed parameters, and retrieval inputs M times within their reasonable ranges given a specific probability density function (PDF) and a specific sampling method for the perturbation samplings. Then we run the cloud retrieval algorithm for these perturbed factors, and a cloud retrieval ensemble can be generated. The cloud retrieval uncertainties are quantified as twice the standard deviation of the cloud retrieval ensemble.

The PDF of perturbation samplings used in this study is a uniform PDF. In order to explore the sensitivity of the determined cloud retrieval uncertainties to the assumed perturbation sampling PDF, we also calculated the cloud retrieval uncertainties for normal and lognormal PDFs. Our analysis shows that when the sample size is as large as 1000, the sensitivity of cloud retrieval uncertainties to the sampling PDF is weak. The sampling method used in this study is a random sampling method with sample size of 1000.

We should note that we have simply assumed that the influential factors for the cloud retrievals are independent. However, this is not true for all factor variables. Correlations could exist between some variables, which then introduce extra errors to this uncertainty quantification.

3. MICROBASE Retrieval Algorithm

Figure 1 shows a diagram of the MICROBASE cloud retrieval process. It contains three parts: the retrieval inputs, retrieval algorithm, and retrieval outputs. The major retrieval inputs are as follows: cloud boundaries determined by millimeter wavelength cloud radar (MMCR), ceilometer and micropulse lidar, equivalent

Table 1. The Empirical Parameters Used in Equations (1)–(4) for the Cloud Retrievals of MICROBASE and Their Potential Variability Ranges Determined With In Situ Data Sets

Parameters	<i>a</i>	<i>b</i>	<i>c</i>	<i>d</i>	<i>g</i>	σ
	(g/m ³)/dBZ	Unitless	$\mu\text{m}/^\circ\text{C}$	$\mu\text{m}/^\circ\text{C}$	Unitless	Unitless
Values	0.097	0.59	75.3	0.5895	0.5556	0.35
Range	0.03–0.22	0.59	75.3	0.23–0.82	0.5–0.6	0.2–0.6

radar reflectivity factor (Z_e) from the MMCR, liquid water path (LWP) from the MWR [Turner *et al.*, 2007], and the cloud temperature (T) from a product (Merged Sounding [Trojan, 2012]) which merges radiosonde observations, surface meteorology, precipitable water vapor from the MWR, and model output from the European Center for Medium-Range Weather Forecasting. The major retrieval outputs are LWC, r_{el} , IWC, and r_{ei} . The retrieval algorithm first determines the cloud phase based on T , which is liquid, ice, and mixed for $T > 0^\circ\text{C}$, $T < -16^\circ\text{C}$, and $-16^\circ\text{C} \leq T < 0^\circ\text{C}$, respectively. Then it derives the liquid and ice properties using empirical regression equations obtained from in situ aircraft measurements with some assumptions. For pure ice clouds, IWC is derived from radar reflectivity at 35 GHz, and r_{ei} is derived from cloud T using

$$\text{IWC} = aZ_e^b \quad (1)$$

$$r_{ei} = (c + dT)/2 \quad (2)$$

where a , b , c , and d are empirical parameters. For pure liquid phase clouds, the LWC follows the change of radar reflectivity vertically with a constraint of LWP from the MWR. The r_{el} is obtained based on LWC by assuming a lognormal droplet size distribution (DSD) and a fixed total number concentration (N). The regression equations for LWC and r_{el} are

$$\text{LWC} = \text{LWP} \frac{Z_e^g}{\sum_{j=1}^M Z_e^g \Delta z} \quad (3)$$

$$r_{el} = \exp(2.5\sigma^2) \left[\frac{3\text{LWC}}{4\pi\rho_L N \exp(4.5\sigma^2)} \right]^{1/3} \quad (4)$$

where g is an empirical parameter, σ is the spectral width of droplet lognormal size distribution, Δz is radar range gate (45 m), and ρ_L is the liquid water density.

We next describe the potential error sources for these cloud retrieval algorithms, including the retrieval inputs, regression parameters, and assumptions.

3.1. Errors in the Inputs

As indicated in Figure 1, the errors associated with input measurements can come from LWP, T , Z_e , and cloud boundaries. We should note that we have not considered the temporal variation of errors in the retrieval inputs, while that could be classified into bias errors. Turner *et al.* [2007] have shown that the uncertainty in the MWR LWP is about 15–30% and 20–30 g/m² for LWP greater and less than 100 g/m², respectively. The error in the cloud temperature depends on the accuracy of the merged sounding product. We assume its accuracy is 0.5 K while the exact error is unknown. The measurement error in Z_e is about 0.5 dBZ, which is the instrument error. Errors set for cloud temperature and radar reflectivity could be overly optimistic. We take the accuracy of cloud base as 7.6 m [Dong *et al.*, 2005] and of cloud top as 45 m (i.e., 1 radar range gate [Dong and Mace, 2003]). The potential range of error in the cloud depth is thus about 53 m. The cloud retrieval uncertainties can also be strongly related to cloud phase and the existence of precipitation or drizzle. For simplicity, we have only considered single-phase (liquid or ice) clouds without precipitation, which is around half of all clouds measured. Uncertainties associated with cloud phases and cloud precipitation will be studied in the future.

3.2. Errors in the Parameters

The errors associated with the regression parameters could come from the following parameters a , b , c , d , g , and σ in equations (1)–(4). Table 1 lists the values of these regression parameters used in MICROBASE. The likely errors in these parameters can be obtained based on in situ aircraft observations as shown in original references of these equations. To better derive empirical relationships, more in situ aircraft

measurements for different types of clouds (vary with cloud types) are definitely needed. However, we should keep in mind that aircraft observations also have their, sometimes significant, uncertainties. In other words, the errors in the relationships we used (even the power relationship) could be much larger [Avramov *et al.*, 2011; Szyrmer *et al.*, 2012].

Equation (1) is from the study of Liu and Illingworth [2000]. This fitting regression equation is mainly based on the aircraft measurements during the Central Equatorial Pacific Experiment, which shows $a = 0.0977$ and $b = 0.596$. These values could vary with cloud types and locations where field campaigns were taken. Protat *et al.* [2007] summarized the in situ observations and show that $a = 0.090$, 0.082 , and 0.103 and $b = 0.580$, 0.554 , and 0.600 for global, midlatitude, and tropics, respectively. Using the same aircraft data as Protat *et al.* [2007] (Figure 1) and assuming parameter b fixed with a value of 0.59 , our analysis shows that parameter a mainly varies between 0.03 and 0.22 . A study by Shupe *et al.* [2005] has indicated that parameter a typically lies between 0.02 and 0.14 in the Arctic, which is slightly smaller than what we found for global. In the real world, parameters a and b could be covariant. For simplicity, we have assumed that only parameter a varies while b is kept fixed in this study.

The regression equation, equation (2), obtained from Ivanova *et al.* [2001], is a least squares fit for ARM and First International Satellite Cloud Climatology Project Regional Experiment (FIRE) measurements. They derived the empirical regression equation based on in situ measurements from both the Forward Scattering Spectrometer Probe (FSSP) and the Particle Measuring System's two-dimensional cloud (2-DC) probes. Uncertainties of the in situ measured r_{ei} at different temperatures have also been indicated in the analysis, from which we have found cloud r_{ei} from both FSSP and 2-DC probes mainly lies between two boundary lines that follow

$$r_{ei} = c + d(T + 73.81) \quad (5)$$

in which c is 15.1 , d is 0.2311 and 0.8211 for the two boundary lines, respectively. The two lines represent the upper and lower boundaries of values of in situ aircraft r_{ei} measurements shown in Ivanova *et al.* [2001]. Note that these values are rough estimates based on very limited aircraft data.

Equation (3) is a regression equation used in Liao and Sassen [1994]. An adiabatic cloud growth model shows that LWC can be related to Z_e through

$$\text{LWC} = (NZ_e/3.6)^{1/1.8} \quad (6)$$

As indicated by Liao and Sassen [1994], strictly speaking, this expression can be approximately applied to nonprecipitating cumulus and stratocumulus clouds for estimating LWC only if N is known. Based on empirical relationships from observations, Liao and Sassen [1994] suggested a value of $N = 100 \text{ cm}^{-3}$. In fact, the value of this reference number is not important for the MICROBASE retrieval since the final LWC will be scaled by LWP from the MWR, which makes the retrieval follow equation (3). Uncertainty in parameter g in equation (3) is unknown. Different values have been used. For example, different from $g = 0.56$ in MICROBASE, Dong *et al.* [1998] and Frisch *et al.* [1995] have used $g = 0.5$. In this study, we simply assume that g can vary between 0.5 and 0.6 .

Equation (4) is obtained using the assumption of lognormal particle size distribution of liquid clouds. No parameters have been used in this equation. Instead, the lognormal DSD, distribution width, and constant cloud number concentration assumptions could introduce errors, which will be discussed in next section.

3.3. Errors in Assumptions

Various assumptions have been used in the cloud retrieval process. The assumptions in MICROBASE include the following: (1) the cloud droplet number concentration does not vary with height; (2) the droplets follow a lognormal particle size distribution with spectral width of 0.35 ; (3) a constant cloud droplet number concentration of 200 cm^{-3} is used for all clouds; (4) the cloud phase is simply dependent on the cloud temperature; (5) the ice crystals are unaggregated, and the shape of ice crystals is planar polycrystals; and (6) regression equations adequately describe the relationship between Z_e and IWC, T and r_{ei} , and Z_e and LWC.

As we have indicated earlier, we only consider single-phase clouds and do not consider errors in the determination of cloud phase (4). In addition, uncertainties associated with assumptions (1) and (5) are not

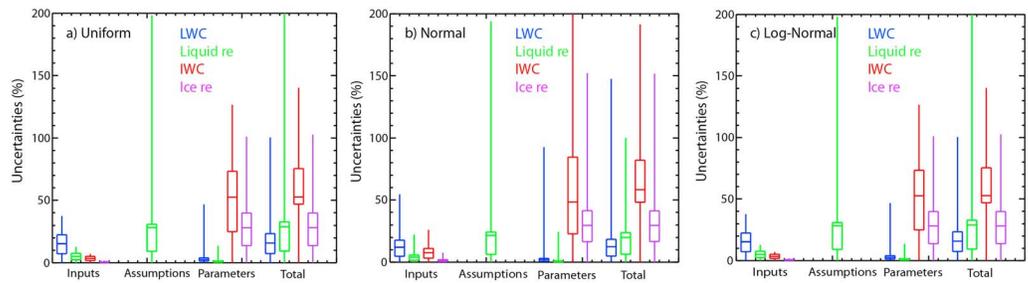


Figure 2. Cloud retrieval relative errors determined by the perturbation method. (a–c) For three different sampling distributions of uniform, normal, and lognormal, respectively. In each panel, four columns are for cloud retrieval uncertainties associated with inputs, assumptions, parameters, and all influential factors, respectively. The blue, green, red, and purple colors represent cloud liquid water content, liquid effective radius, ice water content, and ice effective radius, respectively. For each box with bars, the middle, upper, and lower horizontal lines in the box represent the median, upper quartile, and lower quartile values of the relative errors, respectively; and the upper and lower vertical bars represent the maximum and minimum relative errors, respectively.

considered either in this study although they could be large. Therefore, the uncertainties associated with the assumptions shown in this study could be greatly underestimated.

For the second assumption, the in situ aircraft observations during FIRE Arctic Cloud Experiment in May 1998 have shown that the spectral width (σ) of the lognormal DSD of liquid clouds mainly lies between 0.1 and 0.7 [Shupe *et al.*, 2005]. In this study, we perturb this parameter within range between 0.2 and 0.6. Regarding the total cloud number concentration N , early studies have shown N is generally less than 100 cm^{-3} at the Arctic Beaufort Sea region [Hobbs and Rangno, 1998; Gultepe *et al.*, 2000; Pinto *et al.*, 2001] and the averaged marine stratus N is about 74 cm^{-3} [Miles *et al.*, 2000], as well as that N is about 250 cm^{-3} with standard deviation of 100 cm^{-3} at the ARM Southern Great Plains (SGP) site of Oklahoma in March 2000 [Dong and Mace, 2003]. We vary N within the range of 10 cm^{-3} to 350 cm^{-3} for clouds at the SGP site in this study.

4. Results

Section 3 has described the cloud retrieval algorithm of MICROBASE and indicated the errors in the retrieval inputs, parameters, and assumptions. Next, we perturb these influential factors within their likely ranges to quantify their relative contributions to the uncertainties in the final retrieved fields. For all analyses in this paper, the perturbation runs have been applied to nonprecipitating single-phase clouds at SGP site from 1 January 1999 to 31 December 2001.

We first examine the cloud retrieval uncertainties associated with their inputs. The results are shown in Figure 2a, in which cloud retrieval uncertainties associated with the algorithm inputs are shown in the first column. For each box with bars, the middle, upper, and lower horizontal lines in the box represent the median, upper quartile, and lower quartile values of the relative errors, respectively, and the upper and lower vertical bars represent the maximum and minimum relative errors, respectively. In MICROBASE, IWC and r_{ei} are derived with simple regression equations (equations (1) and (2)) from radar reflectivity and temperature, respectively. Their uncertainties can be easily obtained with an analytical method, which are within 7% and around 1–3% of IWC and r_{ei} means, respectively. A perturbation study confirms these results that mean relative errors in IWC and r_{ei} are about 7% and 1% with standard deviations of 2% and 2%, respectively. Differently, uncertainties in LWC and r_{el} are dependent on both LWP and radar reflectivity; thus, the analytical method does not work. The perturbation analysis shows that the mean errors in LWC and r_{el} are about 15% and 5% with standard deviations of 10% and 3%, respectively.

Figure 2a also shows the cloud retrieval uncertainties caused by the likely errors in the assumptions N and σ . As described earlier, only r_{el} makes use of N and σ in MICROBASE. For other cloud properties, the uncertainty quantification has not considered the contributions from assumptions. With σ fixed, the retrieval uncertainty associated with N is about 15% with standard deviation of 15%. With N fixed, the retrieval uncertainty associated with σ is about 7% with standard deviation of 5%. These results are not shown in Figure 2. When

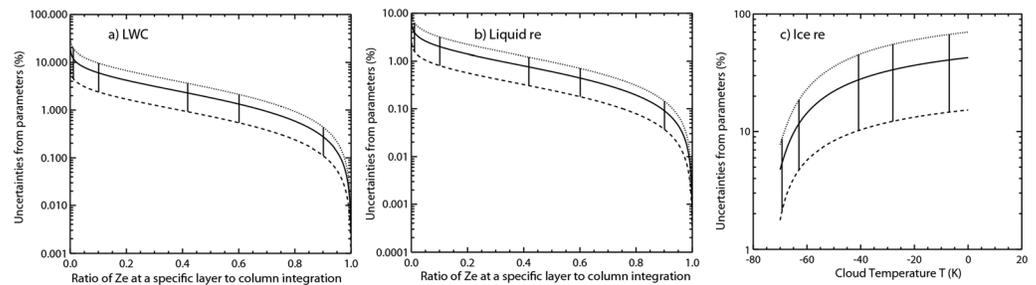


Figure 3. The cloud retrieval uncertainties associated with the empirical regression parameters used in the retrieval algorithms (a) liquid water content (LWC), (b) liquid effective radius (r_{el}), and (c) ice effective radius (r_{ei}). The solid, dotted, and dashed lines are the mean, upper quartile, and lower quartile values of uncertainties from 1000 perturbation runs, respectively.

both σ and N are perturbed, the uncertainties associated with these assumptions are about 30% (Figure 2a) with standard deviation of 50%.

We next examine the statistical uncertainties in retrieved cloud properties by perturbing the parameters used in the algorithms within their likely range as discussed in section 2. As shown in Figure 3, for liquid cloud properties, uncertainties in LWC and r_{el} decrease with increasing relative ratio of radar reflectivity at a specific layer to the column-integrated value. In general, uncertainty in LWC is less than 20% with standard deviation less than 5%, and uncertainty in r_{el} is less than 6% with standard deviation less than 2%. For ice cloud properties, uncertainty in r_{ei} increases with cloud temperature, with statistical mean values between 4% and 30% and standard deviation of about 10%. Since we have used a constant parameter of b only allowing a to vary, uncertainty in IWC does not vary with radar reflectivity, with a statistical mean of about 50% and a standard deviation of 35%.

The total cloud retrieval uncertainties are obtained by perturbing all cloud retrieval influential factors considered in this study together at the same time. The results are shown in Figure 2a. Overall, the total retrieval errors of LWC, r_{el} , IWC, and r_{ei} are about 15%, 30%, 55%, and 30% with most values within the ranges of 5–25%, 5–35%, 40–80%, and 10–40%, respectively. As indicated earlier, we should note that these values could be greatly underestimated due to our limited consideration in cloud retrieval assumptions. Particularly, errors determined for IWC/ r_{ei} could be seriously underestimated without considering the errors in ice crystal habit and ice PSD, which belong to errors associated with the assumptions and empirical parameters.

We also examined the response of the cloud retrieval uncertainties to the error distribution in the influential factors by replacing the uniform distribution with normal and lognormal distributions. As Figures 2b and 2c show, while the retrieval uncertainties do vary with the error distribution of the influential factors, the sensitivities are generally very weak. For all three kinds of error distributions in the influential factors studied here, the retrieval error in LWC mainly comes from the retrieval inputs; the retrieval error in r_{el} is mainly caused by the cloud retrieval assumptions; and the retrieval errors in IWC and r_{ei} are mainly from the empirical regression parameters. Note that these results are for the MICROBASE retrieval algorithm with influential factors considered in this study. Some influential factors have not been considered, including bias errors and some assumptions such as the ice crystal habit.

The uncertainties in Figure 2 are the errors that one would get if the MICROBASE retrievals and their associated uncertainties are realistic but there are many instances when they are not because the retrieval framework is much too simplistic. That is why much larger differences among various cloud retrievals than the uncertainties indicated here have been found [Zhao *et al.*, 2012]. In other words, retrieval uncertainties are highly dependent on the retrieval framework and its associated uncertainties so that we must endeavor going forward to develop realistic retrieval frameworks that truly capture all of the variability in the retrieval process.

Validation of the cloud retrieval uncertainties determined with this perturbation method is even more challenging than the development of cloud retrieval uncertainty quantification methods. Actually, the uncertainties determined by early studies such as intercomparison with limited aircraft observations are often found to be much smaller than the differences of cloud properties among various cloud retrieval products [Zhao *et al.*, 2012]. While knowing this, we still carry out a case evaluation study by using the in situ

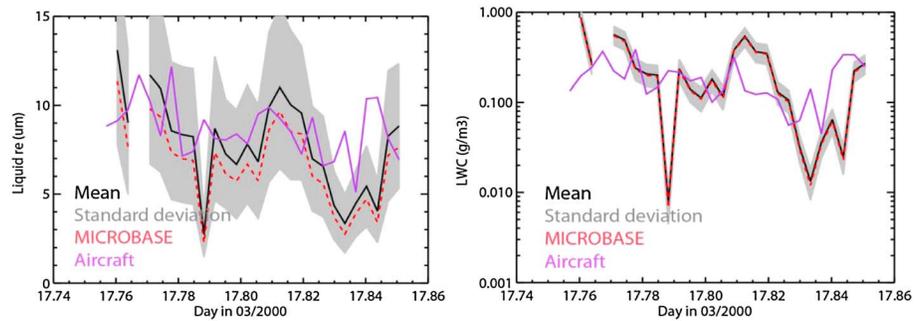


Figure 4. Temporal variation of 1 min averaged cloud droplet effective radius (r_{el}) and liquid water content (LWC) on 17 March 2000 at SGP site. The black, red, and purple lines represent the perturbation ensemble mean, original MICROBASE, and in situ aircraft observations; and gray shadows represent the uncertainties (twice of the standard deviation) determined from the perturbation method.

aircraft observations for stratus clouds on 17 March 2000 at SGP site. This could give us a rough idea whether the perturbation method works reasonably or not. Figure 4 shows the temporal variation of 1 min averaged cloud r_{el} and LWC, in which black, red, and purple lines represent the perturbation ensemble mean, original MICROBASE, and in situ aircraft observations, respectively. Gray shadows in Figure 4 represent the cloud retrieval uncertainties (twice the standard deviation) determined from the perturbation method. For cloud droplet r_{el} , most in situ aircraft data lie within the uncertainties of the ensemble mean, indicating the validity of the perturbation method for quantifying cloud retrieval uncertainty, at least for this limited period. In contrast, the aircraft-observed cloud LWCs are mostly outside of the uncertainties of retrieved LWCs by MICROBASE. However, as we emphasized earlier, the uncertainties determined here could be greatly underestimated due to errors in some assumptions that have not been considered. Also, we should note that the sampling volume between ground-based remote sensing and in situ aircraft observations is different, making this validation more difficult. A more systematic uncertainty quantification method (for different types of clouds) with a collection of various in situ aircraft observations is in process.

5. Retrieval Uncertainties for Different Cloud Regimes

In reality, the errors in the retrieval inputs, regression parameters, and assumptions vary with cloud types. Here we simply assume that they are fixed (most are percentage errors) with cloud types and examine the retrieval relative errors for various cloud regimes.

ARM provides a data product that classifies the cloud-type observed during 1999 to 2001 at the SGP site. This product includes nine types of clouds, which are high clouds, Altostratus, Altocumulus, Stratus, Stratocumulus, Cumulus, Nimbostratus, Deep convective clouds, and other undetermined clouds. This data set makes use of the classification algorithm developed by Wang and Sassen [2001]. This technique

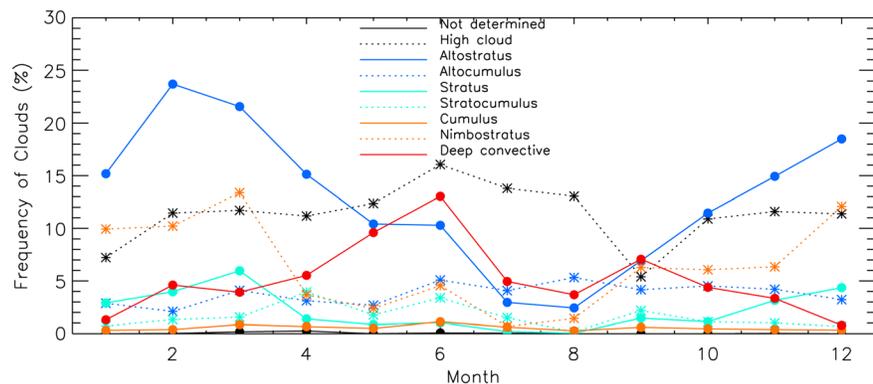


Figure 5. Classification of nine cloud types for measurements from 1999 through 2001 at SGP site. This classification data set is obtained from the ARM product, which is derived based on Wang and Sassen [2001].

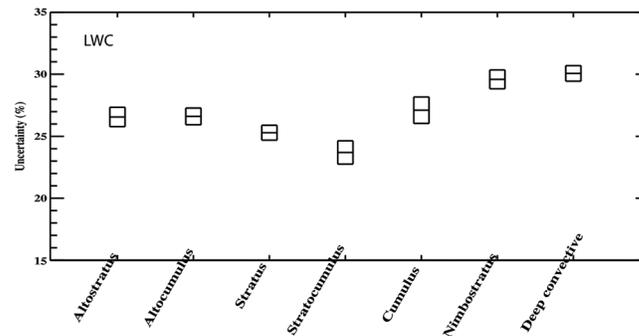


Figure 6. Statistical cloud LWC uncertainties in MICROBASE for seven types of clouds. The middle, upper, and lower lines for each column are mean, upper quartile, and lower quartile values, respectively.

determines cloud phase by combining atmospheric temperature, lidar depolarization ratio and backscattering coefficient, MMCR reflectivity, and MWR LWP. The details of the algorithm can be found in Wang and Sassen [2001] and are not repeated here.

Figure 5 shows the monthly variation of cloud frequency for the nine types of clouds. Stratiform clouds, including Stratus, Nimbostratus, and Altostratus, occur more in winter than in summer. In contrast, convective clouds, including Cumulus and deep convective clouds, have a maximum

occurrence approximately in summer (June) and minimum occurrence in winter (December and January). Stratocumulus occurs more frequently in April through June than other months, and Altocumulus has no clear seasonal variation trend. The total cloud frequency (not shown here) also has a clear seasonal variation, with a maximum in summer and minimum in winter. These seasonal differences could cause the retrieval uncertainties determined with the perturbation method to vary with cloud types, even though the relative errors in the retrieval influential factors are the same.

We examine the uncertainties of LWC for seven types of clouds, which are Altostratus, Altocumulus, Stratus, Stratocumulus, Cumulus, Nimbostratus, and Deep convective clouds. Only nonprecipitating pure liquid phase clouds have been considered. Figure 6 shows the relative cloud retrieval uncertainties determined with the perturbation method, including the mean, lower, and upper quartile values. Most of the uncertainties in LWC are around 20–30%. The uncertainties vary with cloud types, with the highest values for deep convective clouds, nimbostratus and cumulus. This is reasonable since the LWP ranges for these three types of clouds are generally larger than those for other types of clouds. However, the magnitude of variations of cloud uncertainties with cloud types could be much larger than those shown in Figure 6 since the relative errors in the influential factors are generally larger for convective clouds than stratiform clouds. In other words, the same errors in cloud retrieval influential factors assumed in this study have limited the variation of cloud retrieval uncertainties with cloud types.

6. Discussion

This study provides a simple but general approach for cloud retrieval uncertainty quantification. Using MICROBASE as an example, this study illustrates the usage of this method and shows different uncertainty contributions from cloud retrieval inputs, regression parameters, and retrieval assumptions. It also shows different cloud retrieval uncertainties associated with various types of clouds.

Limitations do exist for this perturbation method and current study. First, some assumptions could not be easily quantified and have not been considered, such as the ice crystal habit assumption. Second, we have assumed that the cloud phases are correct in the retrieval algorithm. Third, as we have indicated in section 3, correlations between different variables could exist. A test (not shown here) has shown that the results described in this study do not vary much with the correlations between different influential factors. However, in order to more accurately represent the cloud retrieval uncertainties, correlations between different influential factors should be considered in the future. Fourth, systematic biases cannot be derived with the perturbation method and have not been discussed in this paper. These limitations could make the cloud retrieval uncertainties determined in this study greatly underestimated.

While with above limitations, the results found in this study are still useful to help us determine the cloud retrieval uncertainties, understand and narrow down the causes, and improve the cloud retrieval algorithms. For example, the uncertainties in MICROBASE r_{el} are about 25% and mainly caused by the retrieval assumptions. To reduce the cloud retrieval uncertainties in r_{el} , we could classify clouds into different cloud types based on a large amount of in situ observations and apply the corresponding more reliable assumptions.

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References

- Ackerman, T. P., and G. M. Stokes (2003), The atmospheric radiation measurement program, *Phys. Today*, *56*, 38–44.
- Avramov, A., et al. (2011), Toward ice formation closure in Arctic mixed-phase boundary layer clouds during ISDAC, *J. Geophys. Res.*, *116*, D00T08, doi:10.1029/2011JD015910.
- Comstock, J. M., et al. (2007), An intercomparison of microphysical retrieval algorithms for upper-tropospheric ice clouds, *Bull. Am. Meteorol. Soc.*, *88*, 191–204, doi:10.1175/BAMS-88-2-191.
- Deng, M., and G. G. Mace (2008), Cirrus cloud microphysical properties and air motion statistics using cloud radar Doppler moments: Water content, particle size, and sedimentation relationships, *Geophys. Res. Lett.*, *35*, L17808, doi:10.1029/2008GL035054.
- Dong, X., and G. G. Mace (2001), Profiles of low-level stratus cloud microphysics deduced from ground-based measurements, *J. Atmos. Oceanic Technol.*, *20*, 42–53.
- Dong, X., and G. G. Mace (2003), Arctic stratus cloud properties and radiative forcing derived from ground-based data collected at Barrow, Alaska, *J. Clim.*, *16*, 445–461.
- Dong, X., T. P. Ackerman, and E. E. Clothiaux (1998), Parameterizations of microphysical and radiative properties of boundary layer stratus from ground-based measurements, *J. Geophys. Res.*, *102*, 31,681–31,693.
- Dong, X., P. Minnis, and B. Xi (2005), A climatology of midlatitude stratus clouds from ARM SGP site: Part I: Macrophysical, microphysical and radiative properties, *J. Clim.*, *18*, 1391–1410.
- Dunn, M., K. L. Johnson, and M. P. Jensen (2011), The Microbase value-added product: A baseline retrieval of cloud microphysical properties. DOE/SC-ARM/TR-095. [Available at http://www.arm.gov/publications/tech_reports/doe-scp-arm-tr-095.pdf.]
- Frisch, A. S., C. W. Fairall, and J. B. Snider (1995), Measurement of stratus cloud and drizzle parameters in ASTEX with K-band Doppler radar and a microwave radiometer, *J. Atmos. Sci.*, *52*, 2788–2799.
- Garrett, T. J., and C. Zhao (2013), Ground-based remote sensing of thin clouds in the Arctic, *Atmos. Meas. Tech.*, *6*, 1227–1243, doi:10.5194/amt-6-1227-2013.
- Gultepe, I., G. Isaac, D. Hudak, R. Nissen, and J. W. Strapp (2000), Dynamical and microphysical characteristics of Arctic clouds during BASE, *J. Clim.*, *13*, 1225–1254.
- Hobbs, P. V., and A. L. Rangno (1998), Microstructures of low and middle-level clouds over the Beaufort Sea, *Q. J. R. Meteorol. Soc.*, *124*, 2035–2071.
- Hogan, R. J., D. P. Donovan, C. Tinel, M. A. Brooks, A. J. Illingworth, and J. P. V. Poiras Baptista (2006), Independent evaluation of the ability of spaceborne radar and lidar to retrieve the microphysical and radiative properties of ice clouds, *J. Atmos. Oceanic Technol.*, *23*, 211–227.
- Huang, D., C. Zhao, M. Dunn, X. Dong, G. G. Mace, M. P. Jensen, S. Xie, and Y. Liu (2012), An intercomparison of radar-based liquid cloud microphysics retrievals and implications for model evaluation studies, *Atmos. Meas. Tech.*, *5*, 1409–1424, doi:10.5194/amt-5-1409-2012.
- Intergovernmental Panel on Climate Change (2007), *Climate Change 2007: IPCC Fourth Assessment Report*, Cambridge Univ. Press, Cambridge, U. K.
- Ivanova, D. C., D. L. Mitchell, W. P. Arnott, and M. Poellot (2001), A GCM parameterization for bimodal size spectra and ice mass removal rates in mid-latitude cirrus clouds, *Atmos. Res.*, *59*, 89–113.
- Leith, C. E. (1974), Theoretical skill of Monte Carlo forecasts, *Mon. Weather Rev.*, *102*, 409–418.
- Liao, L., and K. Sassen (1994), Investigation of relationships between Ka-band radar reflectivity and ice and liquid water contents, *Atmos. Res.*, *34*, 231–248.
- Liu, C.-L., and A. J. Illingworth (2000), Toward more accurate retrievals of ice water content from radar measurements of clouds, *J. Appl. Meteorol.*, *39*, 1130–1146.
- Mace, G. G., T. P. Ackerman, P. Minnis, and D. F. Young (1998), Cirrus layer microphysical properties derived from surface-based millimeter radar and infrared interferometer data, *J. Geophys. Res.*, *103*, 23,207–23,216, doi:10.1029/98JD02117.
- Mace, G. G., A. J. Heymsfield, and M. R. Poellot (2002), On retrieving the microphysical properties of cirrus clouds using the moments of the millimeter-wavelength Doppler spectrum, *J. Geophys. Res.*, *107*(D24), 4815, doi:10.1029/2001JD001308.
- McFarlane, S. A., K. F. Evans, and A. S. Ackerman (2002), A Bayesian algorithm for the retrieval of liquid water cloud properties from microwave radiometer and millimeter radar data, *J. Geophys. Res.*, *107*(D16), 4317, doi:10.1029/2001JD001011.
- Miles, N. L., J. Verlinde, and E. E. Clothiaux (2000), Cloud droplet size distributions in low-level stratiform clouds, *J. Atmos. Sci.*, *57*, 295–311, doi:10.1175/1520-0469(2000)057<0295:CDSDL>2.0.CO;2.
- Pinto, J. O., J. A. Curry, and J. M. Intrieri (2001), Cloud-aerosol interactions during autumn over Beaufort Sea, *J. Geophys. Res.*, *106*(D14), 15,077–15,097, doi:10.1029/2000JD900267.
- Posselt, D., T. S. L'Ecuyer, and G. L. Stephens (2008), Exploring the error characteristics of thin ice cloud property retrievals using a Markov chain Monte Carlo algorithm, *J. Geophys. Res.*, *113*, D24206, doi:10.1029/2008JD010832.
- Protat, A., J. Delanoë, D. Bouniol, A. J. Heymsfield, A. Bansemmer, and P. Brown (2007), Evaluation of ice water content retrievals from cloud radar reflectivity and temperature using a large airborne in situ microphysical database, *J. Appl. Meteorol. Climatol.*, *46*, 557–572.
- Shupe, M. D., T. Uttal, and S. Y. Matrosov (2005), Arctic cloud microphysics retrievals from surface-based remote sensors at SHEBA, *J. Appl. Meteorol.*, *44*, 1544–1562, doi:10.1175/JAM2297.1.
- Szyrmer, W., A. Tatarevic, and P. Kollias (2012), Ice clouds microphysical retrieval using 94-GHz Doppler radar observations: Basic relations within the retrieval framework, *J. Geophys. Res.*, *117*, D14203, doi:10.1029/2011JD016675.
- Troyan, D. (2012), Merged sounding value-added product. DOE/SC-ARM/TR-087. [Available at http://www.arm.gov/publications/tech_reports/doe-scp-arm-tr-087.pdf.]
- Turner, D. D. (2005), Arctic mixed-phase cloud properties from AERI lidar observations: Algorithm and results from SHEBA, *J. Appl. Meteorol.*, *44*, 427–444.
- Turner, D. D., S. A. Clough, J. C. Liljegren, E. E. Clothiaux, K. Cady-Pereira, and K. L. Gaustad (2007), Retrieving liquid water path and precipitable water vapor from Atmospheric Radiation Measurement (ARM) microwave radiometers, *IEEE Trans. Geosci. Remote Sens.*, *45*(11), 3680–3690.
- Wang, Z., and K. Sassen (2001), Cloud type and macrophysical property retrieval using multiple remote sensors, *J. Appl. Meteorol.*, *40*(10), 1665–1682.
- Wang, Z., and K. Sassen (2002), Cirrus cloud microphysical property retrieval using lidar and radar measurements. Part I: Algorithm description and comparison with in situ data, *J. Appl. Meteorol.*, *41*, 218–229.
- Xie, S., et al. (2011), Focus group proposal whitepaper: ASR quantification of uncertainty in cloud retrievals (QUICR) focus group, Dept. Of Energy, Washington, D. C. [Available at http://asr.science.energy.gov/science/working-groups/fg/docs/CLWG_QUICR.pdf.]

- Zhao, C., et al. (2011), ARM cloud retrieval ensemble data set (ACRED), *Tech. Rep. DOE/SC-ARM-TR-099*, Dept. Of Energy, Washington, D. C. [Available at https://www.arm.gov/publications/tech_reports/doe-sc-arm-tr-099.pdf.]
- Zhao, C., et al. (2012), Toward understanding of differences in current cloud retrievals of ARM ground-based measurements, *J. Geophys. Res.*, 117, D10206, doi:10.1029/2011JD016792.