A Method for Assessing Relative Skill in Retrieving Cloud and Precipitation Properties in Next-Generation Cloud Radar and Radiometer Orbiting Observatories

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ABSTRACT

A Bayesian Markov chain Monte Carlo (MCMC) algorithm is utilized to compare the skill of an A-Train-like observing system with a cloud, convection, and precipitation (CCP) observing system like that contemplated for the 2020s by the 2017 National Academy of Sciences Decadal Survey. The main objective is to demonstrate a framework for observational trade space studies. This initial work focuses on weakly precipitating warm shallow cumulus constructed from in situ data. Radiative computations are based on Mie theory with spherical assumptions. Simulated measurements in the CCP configuration consist of W- and Ka-band radar reflectivity and path-integrated attenuation, 31 and 94 GHz brightness temperatures (T_b), and visible and near-infrared reflectances. The collection of measurements in the *CloudSat* configuration is identical, but includes a single 94 GHz radar frequency, and the uncertainty in the 94 GHz microwave brightness temperature is increased to mimic the *CloudSat* T_b product. The experiments demonstrate that it remains a challenge to diagnose cloud properties in the presence of light rain because of the tendency of microwave remote sensing to respond to the higher moments of the hydrometeor populations. Rain properties are significantly better constrained than cloud properties, even in the optimal CCP configuration. The addition of Ka-band measurements places substantial constraints on the precipitation rain effective radius and rain rates. The T_b offers important information regarding the column-integrated condensate mass, the measurement accuracy of which appears more likely to affect the retrievals of clouds with low liquid water path. The constraints provided by reflectances are largely restricted to regions near the cloud top, particularly in the raining cases.

1. Introduction

The cloud feedback to changes in Earth's climate system remains a critical challenge, and constitutes the largest source of uncertainty in climate projection (IPCC 2013). In the decadal survey for Earth Science and Applications from Space (ESAS; National Academies of Sciences, Engineering, and Medicine 2018) released in 2017, significantly reducing the cloud feedback uncertainties falls within the category of the "most important" Earth science objectives. A dominant contributor to the cloud feedback

uncertainties is marine boundary layer clouds (Bony and Dufresne 2005; Sherwood et al. 2014). MBL clouds exert a significant influence on Earth's radiative balance due to their extensive coverage over the global oceans (Hartmann et al. 1992; Haynes and Stephens 2007).

The complexity of estimating the climate forcing by MBL clouds arises from the wide range of spatial and temporal scales at which various physical processes act. Macrophysical properties of MBL clouds (e.g., cloud fraction and liquid water path) that determine their radiative effect depend on the large-scale meteorological conditions, such as lower-tropospheric stability and free-tropospheric relative humidity (Ackerman et al. 2004). They also respond to microphysical aerosol perturbations within cloud elements that are fundamentally coupled to precipitation

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production (Albrecht 1989; Stevens and Feingold 2009; Christensen and Stephens 2011; Chen et al. 2015; Mace and Abernathy 2016). In fact, under consistent environmental conditions, the sign of liquid water path (LWP) susceptibility to changes in aerosol can be opposite in raining versus nonraining conditions (Chen et al. 2014). While a faithful depiction of warm rain formation in climate models is critical, models tend to produce rain too efficiently and overestimate the occurrence of light rain compared with observations (Stephens et al. 2010). Such model biases result from multiple sources, among which a vital one is the subgrid parameterizations of microphysical processes that govern the time scale of the conversion from cloud droplets to rain. Two microphysical schemes of particular importance, autoconversion and accretion, are parameterized in terms of microphysical properties such as cloud/rainwater mixing ratio and cloud number concentration (e.g., Beheng 1994; Khairoutdinov and Kogan 2000). Autoconversion represents the coalescence among cloud droplets, and accretion represents the collection of cloud droplets by existing rain embryos. These bulk parameterizations were originally developed for cloud resolving models, and parameter values are subject to uncertainties (Wood 2005; Posselt 2016; Posselt et al. 2019). Enhancement factor tunings are used in these schemes in coarse-resolution GCMs to account for the subgrid variance and covariance of microphysics, the constraints of which rest upon observations in essence (Lebsock et al. 2013).

Many studies have shown that the treatment of autoconversion schemes can significantly impact how models represent rain formation and cloud properties such as liquid water path (e.g., Suzuki et al. 2015; Takahashi et al. 2017; Jing et al. 2017). Moreover, the simulation of cloud–aerosol interactions in GCMs is highly sensitive to the autoconversion assumption (Gettelman 2015; Michibata and Takemura 2015), which has a strong nonlinear dependence upon cloud number concentration and hence is sensitive to the local aerosol properties. While accretion has been given less scrutiny, a realistic balance between the contribution from autoconversion and accretion processes to the formation of precipitation is pivotal to alleviate the overestimated radiative responses to aerosol perturbations in GCMs (Posselt and Lohmann 2009; Gettelman et al. 2015).

Advances in process-level understanding of MBL clouds necessitate the joint observation of cloud and precipitation properties. For example, the parameterization of accretion rates entails the knowledge of both cloud and rain condensate mass. Mace et al.

(2016) retrieved co-occurring cloud and rain microphysics with A-Train data, and showed that the measurements provided information on the autoconversion and accretion rates, but that these quantities could only be estimated with large uncertainties. Suzuki et al. (2011; 2015) also demonstrates that the representation of cloud-to-rainwater processes in models may be improved with A-Train observations by combining the vertically resolved radar reflectivity from *CloudSat* (Stephens et al. 2008) and optical properties derived from the Moderate Resolution Imaging Spectroradiometer (MODIS; Platnick et al. 2003). While the A-Train has provided critical global insight on MBL cloud properties, the nexus of aerosol, cloud, and precipitation microphysics, and cloud-scale dynamics, is out of reach of A-Train observations and, therefore, remains largely unobserved.

Motivated by these issues among others, ESAS 2017 put forward designated program elements to address observational needs with the highest priorities, one of which is clouds, convection, and precipitation (CCP) for which the global characterization of cloud and precipitation structure in MBL clouds is deemed an essential component. Candidate measurement approaches recommended in ESAS 2017 include W- and Ka-band Doppler radar systems, multifrequency passive microwave measurements as well as spectral reflectances.

Planning the next-generation cloud observing systems requires a means by which the science benefits can be weighed against cost and complexity. Given constrained budgets and finite resources, it is critically necessary to define an optimal observing system with the goal to reduce technical complexities and risks and also maximize scientific benefits within cost constraints. Motivated by this objective in light of the critical science surrounding precipitation processes in shallow clouds, we explore one such mechanism for conducting trade studies. We use Markov chain Monte Carlo methodologies to perform observing system simulation experiments (OSSEs) with shallow, lightly precipitating cumulus clouds as an example of such trade studies. Building upon the recommendations for CCP in ESAS 2017, we envision extending the measurements available in the A-Train with the intention of expanding the range of hydrometeor size distributions that can be constrained. Our candidate simulated measurements include W- and Ka-band radar reflectivity, path-integrated attenuation at those frequencies, 31 and 94 GHz brightness temperatures, as well as visible and near-infrared reflectance. Microwave brightness temperatures could be obtained from separate radiometers or by adding

radiometer technology to the radar receiver. Visible and near-infrared reflectances could be provided by a dedicated imager or from imagery of opportunity such as from geostationary satellites. The CCP mission is just entering the study phase where a wide spectrum of observing architectures are to be intensively studied. Therefore, we envision a notional measurements system based broadly on the requirements defined by the Aerosol-Cloud-Ecosystem (ACE) project ([National Research Council 2007](#)) to indicate the observing system with the additional Ka-band observations for illustration purposes. While Doppler velocity, and lidar measurements and additional types of imagers will ultimately be considered during the study phase of the CCP mission, we defer their consideration to future work.

2. Data

Three marine boundary layer cloud cases were selected from two field campaigns, which are the Rain in Cumulus over the Ocean (RICO; [Rauber et al. 2007](#)) and NASA Integrated Precipitation and Hydrology Experiment (IPHEX; [Barros et al. 2014](#)). RICO was designed to mainly capture the shallow MBL clouds within the western Atlantic trade wind zone, while IPHEX sampled maritime clouds over the Gulf Stream and orographic precipitation over the southeast United States. Observation-based vertical cloud and precipitation profiles ([Figs. 1–3](#)) were generated by combining in situ aircraft data from flight legs at various altitudes during an approximately 1 to 2-h periods of time when the in situ aircraft were profiling MBL clouds. Because the aircraft tended to step vertically in ~ 1000 foot increments, a 350-m vertical resolution is used for the profiles. Data are obtained from three individual cases: 12 May 2014 during IPHEX and 7 and 14 January 2005 during RICO. Hereafter, these are referred to as IPHEX 0512, RICO 0107, and RICO 0114, respectively.

To construct the vertical profiles, we identified periods when the in situ aircraft conducted a series of stepped-level legs or spirals that essentially profiled the cloud and precipitation microphysical properties over a small region. This ensured the cloud thermodynamic and shear environments were approximately unchanging. Using data from cloud droplet probes and measurements from 2D precipitation spectrometers [see [Rauber et al. \(2007\)](#) and [Barros et al. \(2014\)](#) for a detailed list of probes employed on the aircraft], we created cloud mode and precipitation mode modified gamma fits (see [section 3](#)) to the probe data averaged over approximately 5 s intervals. Both experiments

include bulk liquid water content measurements in addition to the droplet spectrometers, and we used only fitted gamma particle size distributions (PSDs) that, when integrated, matched the bulk water measurements to within a factor of 2. Representative cloud and precipitation mode microphysics in 350 m vertical increments were then produced by first calculating averages of the liquid water content, effective radius, and droplet number concentrations of all 5 s particle size distributions within a vertical increment. Representative cloud and precipitation mode PSDs were then chosen from among the observations by finding the mode-specific PSD that minimized the summed squared differences of the liquid water content, effective radius, and droplet concentration for the cloud and precipitation droplet modes. Given sufficient particle in situ measurements collected over a vertical interval that reasonably profiles a hydrometeor layer, this approach can be generally applied to any cloud type to document the vertical properties of hydrometeor layers. Forward calculating remote sensing measurements could then allow for experimentation with various observing systems. However, the typical uncertainties associated with ice crystal scattering properties would need to be accounted for were the method applied to mixed phase or ice clouds.

The chosen cases represent typical cloud scenes with various vertical structures, including clouds with negligible precipitation, clouds with precipitation near cloud top, and clouds with precipitation primarily concentrated near the bottom of the cloud. RICO 0107 has three contiguous vertical layers with maximum simulated W-band radar reflectivity of approximately -17 dBZ, and hence, it is treated as a cloud-only case in the retrievals. Relatively small amounts of precipitation were present in the other cases, as two-way path-integrated attenuation (PIA) at 94-GHz is about 8 and 3.8 dB in RICO 0114 and IPHEX 0512, respectively. The rain rates R of a single layer vary from 28 to 37 mm day $^{-1}$ within the three layers near cloud top in RICO 0114. Observables used in the retrievals are simulated using forward models that are described in [section 3c](#). The primary goal of this paper is to present a methodology by which observing systems can be evaluated for their constraint of the cloud and precipitation microphysical quantities critical to precipitation producing processes in warm shallow clouds. Because the cloud and precipitation microphysics are known, we are able to evaluate quantities retrieved from forward calculated observables. Furthermore, because the vertical profiles are derived from observations and not models,

FIG. 1. The synthetic observational profiles of (top) rain and (middle) cloud mode liquid water content, number concentration, and effective radius generated with in situ data collected from 2017 to 2107 UTC 14 Jan 2005 during the RICO field campaign. Black and red lines in the bottom panel, respectively, indicate the corresponding simulated W- and Ka-band radar reflectivity.

FIG. 2. As in Fig. 1, but for the profile generated from in situ data collected from 1825 to 1505 UTC 7 Jan 2005 during the RICO field campaign.

FIG. 3. As in Fig. 1, but for the profile generated from in situ data collected from 1259 to 1350 UTC 12 May 2014 during the IPHEX field campaign.

we can be reasonably confident that the cases are representative of what would be found in nature versus what might be produced from a model parameterization. In spite of the benefits, it must be acknowledged there exist limitations in the case studies and forward calculated observables that we will discuss as we proceed.

3. Methodology

Following Mace et al. (2016) and Posselt et al. (2017), we assume the presence of distinct rain and cloud droplet modes. In each, the PSD takes the form of a modified gamma with distinct parameters in each vertical cloud layer:

$$N(D) = N_{x,i} \left(\frac{D}{D_{x,i}} \right)^{\alpha_i} \exp \left(-\frac{D}{D_{x,i}} \right), \quad (1)$$

where i indicates rain (p) or cloud mode (c). The N_x is a characteristic number associated with the total number concentration; D_x and α represent, respectively, the characteristic diameter and shape parameter. Vertically resolved PSD parameters are directly retrieved from observations with MCMC algorithms and converted to liquid water content (q), total number concentration (N_d), and effective radius (r_e). The microphysical variables can be calculated from the gamma PSDs as follows:

$$\text{LWC}_i = a_m N_{x,i} D_{x,i}^{b_m+1} \Gamma(\alpha_i + b_m + 1), \quad (2)$$

$$N_{d,i} = N_{x,i} D_{x,i} \Gamma(\alpha_i + 1), \quad (3)$$

$$r_{e,i} = \frac{1}{2} D_{x,i} (\alpha_i + b_a + 1), \quad (4)$$

where a_m and b_m are the parameters in the mass-dimensional relationship (assuming liquid spheres, $a_m = \pi/6$ and $b_m = 3$), and b_a is the exponent in the area-dimensional relationship (for spheres, $b_a = 2$). Because cloud and rain droplets are assumed to be spherical, a_m , b_m , and b_a are all constant. A spherical shape assumption can be applied to drops with radii smaller than approximately $500 \mu\text{m}$ beyond which the shape may be considered as an oblate spheroid (Pruppacher and Pitter 1971; Matrosov 2009). We acknowledge that the adoption of a spherical assumption in this work limits the subject to be liquid-phased clouds with light rain. Contrary to being constant, significant uncertainties are associated with mass-dimensional and area-dimensional relationships for ice particles (Posselt and Mace 2014; Xu and Mace 2017; Mascio et al. 2017). Application of the

present work to heavier rain and ice phase will require more advanced scattering approximations in forward models that do not premise on a spherical shape. The framework we outline herein can be adapted to take into account heavier precipitation by adopting appropriate radiative parameters and accounting for their uncertainty.

In the nonprecipitating case (RICO 0107) only the parameters of the cloud droplet mode are estimated, while both rain and cloud modes are estimated in the cases with precipitation. Even with the full set of proposed active and passive measurements, the problem remains ill posed. For example, there exists a total of 30 parameters to be retrieved in a 5 cloudy-layer raining case: the product of the number of free bimodal PSD parameters and the number of cloudy layers. Further constraints may be provided by taking into account the vertical correlations among PSD parameters. However, the ill-constrained nature will not be changed, unless assumptions are made to reduce the dimensions involved in the problem, such as assuming a constant cloud number concentration that does not vary vertically in retrievals (Mace and Sassen 2000; Leinonen et al. 2016).

a. MCMC algorithms

Bayesian approaches have been utilized to estimate cloud and precipitation properties from remote sensing observations, assess the information contained in measurements, as well as the effect of forward model uncertainties (Evans et al. 1995; Bauer 2001; McFarlane et al. 2002; Grecu and Olson 2006; Posselt and Mace 2014; Xu and Mace 2017; Leinonen et al. 2018; among many others). In addition to the optimal estimation methodology (OE; Rodgers 2000), there is an increasing application of Markov chain Monte Carlo algorithms in the realm of atmospheric sciences, which is also based on Bayes's theorem (e.g., Tamminen and Kyrölä 2001; Posselt et al. 2008; Posselt and Vukicevic 2010; Posselt and Mace 2014; Posselt 2016; Posselt et al. 2017). Assuming that indirect measurements y contain information regarding geophysical parameters of interest x , the retrieval is implemented by combining the prior and measurements along with a set of forward models to relate x and y . The posterior probability density function $P(x|y)$ is typically provided via Bayes's theorem as a conjunction of conditional probabilities:

$$P(x|y) = \frac{P(y|x)P(x)}{P(y)}, \quad (5)$$

where $P(x)$ represents the prior knowledge of retrieved parameters, and $P(y)$ represents the probability density

of observations (i.e., the “truth”); $P(y|x)$ gives the likelihood that estimated parameters produce observations that are equivalent to the measurements produced by the “true” parameters. The uncertainties of retrieval parameters can be estimated by calculating the width of solution information space represented in $P(x|y)$.

OE assumes the probability distributions in Bayes’s relationship are all Gaussian; as such, there is a single maximum likelihood point in the solution space. The maximum likelihood solution is obtained by minimizing a quadratic cost function that implicitly assumes the forward models are linear or can be linearized around a given parameter set x . MCMC can be implemented in a flexible way, in that any reasonable form may be assigned to the prior and likelihood probability distributions without requiring linearity in forward models or the existence of a single maximum likelihood solution. The flexibility inherent in an MCMC-based retrieval allows for generation of a realistic and complete solution space.

MCMC algorithms map the posterior parameter space with a random walk that is made up of successive iterations (described below), and the sequence of iterations forms the Markov chain. Multiple independent chains, started from different points (i.e., first guess values) in the parameter space, are generally employed in a single MCMC experiment to allow the solution space to be explored efficiently. The operation of an MCMC algorithm may be summarized in the following steps:

- (i) In each iteration, a candidate parameter set ($\hat{x}$) is randomly drawn from a “proposal” distribution, $[q(\hat{x}, x_i)]$, that is centered on the current parameter set (x_i). This proposal distribution represents the transition probability that the Markov chain moves from the state of x_i to proposed $\hat{x}$. A Gaussian PDF is used as the proposal distribution in our algorithms.
- (ii) Forward model outputs ($\hat{y}$) are generated from the candidate parameter sets, and are used to compute the likelihood $P(\hat{y}|\hat{x})$.
- (iii) To determine whether $\hat{x}$ is accepted as a new sample in the posterior distribution, we compute the acceptance ratio, which is defined as

$$\rho = \frac{P(\hat{x})P(\hat{y}|\hat{x})q(\hat{x}, x_i)}{P(x_i)P(y_i|x_i)q(x_i, \hat{x})}. \quad (6)$$

The $q(\hat{x}, x_i)$ is proposal distribution as introduced in step (i). Here, $q(x_i, \hat{x})$ represents a similar probability of movement but in the converse direction, which is from

$\hat{x}$ back to x_i . If the proposal distribution is symmetrical, $q(\hat{x}, x_i)$ is equal to $q(x_i, \hat{x})$, and then the acceptance ratio will simply depend on the prior and likelihoods. The proposed parameter set is accepted with the probability $Q(\hat{x}, x_i) = \min(\rho, 1)$.

If the forward measurables generated with the proposed parameter set have an improved fit to measurements ($\rho > 1$), the proposed parameters will be accepted immediately. If not, ρ will be compared with a random number from a uniform distribution. The proposed set will still be accepted as a new sample in the posterior PDF, if ρ is larger than the random number. Otherwise, the proposed parameter set will be rejected. As designed, the region with high probability is preferred in the sampling process, while the region with low probability is intended to be avoided. Furthermore, the probabilistic accept/reject procedure allows the Markov chain to move away from local probability maxima, which renders a solution space with multiple modes possible and differentiates MCMC from an OE methodology.

Following Posselt et al. (2017), we account for the vertical covariance of cloud properties using a Gaussian decorrelation function to correlate the perturbation of parameters layer to layer (refer to their appendix A for details). It was found that 100 000 iterations are necessary to sample the solution space of parameters that are not in the form of a Gaussian (e.g., Posselt et al. 2008). Given the fact that the appearance of non-Gaussian distribution is far from rare in terms of the parameters considered, each chain is set to contain 100 000 iterations, while the number of MCMC chains that are run simultaneously is reduced from 24 in previous work (Posselt et al. 2017) to 12, which proves to be sufficient to generate a robust posterior sampling space. The major improvements in the algorithms are twofold. We find that perturbing parameters with large natural variability (e.g., cloud number concentration) in linear space may cause biases in the retrieval results, as the solution space cannot be effectively explored with efficiency. Hence perturbations of all the PSD parameters are conducted in log space, which allows for rapid moves of parameters with values spanning a wide range. Moreover, the prior is cast in geophysical parameter space [i.e., Eqs. (2)–(4)] instead of PSD space [Eq. (1)], by means of which determining a representative prior from observations becomes more feasible.

b. Observing systems and the prior

The complete candidate observing system that we consider consists of radar reflectivities, microwave radiometer brightness temperatures and PIA at multiple frequencies as well as visible and near-infrared

reflectances. In an actual observing system, or in an observing system simulation experiment that attempts to fully evaluate a measurement architecture, one would normally need to consider both the vertical and horizontal resolution mapped onto the horizontal and vertical heterogeneity of the cloud systems. For radar remote sensing, this would account for footprints that are only partially filled with cloud, or in which cloud has a nonuniform distribution; otherwise known as nonuniform beamfilling (NUBF). One would also need to account for uncertainties due to measurement noise and other issues such as forward model error, which would be present regardless of the vertical and horizontal resolution of the measurement. The latter is what we consider in this work—what we term the pixel-level retrieval uncertainties—and we have decided not to address NUBF. While NUBF is a key aspect of an observing system that must be considered eventually, the degree to which it is a factor depends on the specifics of the measurement system (e.g., orbit altitude, antenna size). Our goal in this work is to illustrate a method for evaluating the capacity for an observing system to represent the retrieval errors at the pixel level. We reserve study of the effects of NUBF for later work, and conduct only a few very simple experiments to illustrate the degree to which it may be a factor in our study.

There are two configurations in our experiments: one corresponding to A-Train, including *CloudSat* and MODIS; and another that assumes a next-generation observing system that we will refer to as CCP following the ESAS 2017 designation for the clouds–convection–precipitation concept:

- The *CloudSat*-like configuration is composed of a 94-GHz radar that provides reflectivity, Tb, and PIA, along with visible and near-IR reflectances (e.g., from MODIS). The CCP configurations include the addition of a Ka-band radar that also provides reflectivity, PIA, and Tb measurements. The difference between W- and Ka-band effective reflectivity is due to differential attenuation for scatters that are much smaller than radar wavelength. Out of Rayleigh regime (diameter of droplets $> \sim 500 \mu\text{m}$ at 94 GHz), the differential reflectivity is determined by both scattering and attenuation properties, which depend on the frequencies (Lhermitte 1990). A dual-frequency combination of W and Ka bands is likely to reduce ambiguities in rainfall microphysical properties when droplet sizes in excess of $\sim 500 \mu\text{m}$ contribute significantly to the droplet distribution properties. The constraints provided by the additional active microwave frequency are expected to emerge primarily in the precipitating cases.

- We assume higher accuracies for Tb measurements in the CCP-like configuration, since there was no radiometer on the *CloudSat* platform and the 94-GHz Tbs are experimental products that were generated from vicariously calibrated radar receiver noise. Microwave radiometers, whether provided by standalone instruments or built specifically into the radar receiver of both frequencies, are considered to be a member of future observing system and thus the information would be more precise than provided by *CloudSat*.
- The sensitivity of the CCP radar system is increased relative to *CloudSat*, with W-band minimum detectable reflectivity reduced to -35 dBZ from -30 dBZ . The Ka-band minimum detectable reflectivity is set to -10 dBZ following the requirements specified from the ACE study (NASA 2015).
- The specific baseline uncertainty for each observation is summarized in Tables 1 and 2. Note the magnitude of Tb and PIA uncertainties is the sum of the LWP-scaled variances reported by Lebsock and Suzuki (2016), and the accuracies of instruments listed in the tables. The largest PIA uncertainty of about 1 dB exists in case RICO 0114, where the total LWP is 573.7 g m^{-2} .

In addition to the observations, the prior can also exert considerable influence on the posterior PDFs in Bayesian retrievals. When observations afford limited amounts of unique information, retrieval outcomes will be primarily driven by the prior. We apply a scene-consistent prior in the cloud space of LWC, N_d , and r_e throughout the MCMC experiments. To generate a realistic prior, the observational data pertaining to shallow cumulus were selected from the RICO, IPHEX, and OLYMPLEX datasets. Cloud mode quantities (i.e., LWC, N_d , and r_e) are derived by integrating the PSDs over the droplet size from 0 up to $70 \mu\text{m}$, the integral of PSDs above which determines the same quantities for the rain mode. Gaussian PDFs are fitted to the log-scaled in situ cloud and rain properties, which approximate a lognormal prior in linear space. We run a MCMC experiment using no observations, in which case the posterior sampling space maps the prior assumed in the retrievals (Fig. 4). The a priori information is presented in terms of the means of these distributions, so the contributions from observations can be distinguished by comparing the solution space of the prior-only experiment and that of experiments with the addition of observations.

c. Forward models

Focusing on liquid water clouds in this study, radar reflectivities are derived by integrating Mie backscatter

TABLE 1. Uncertainties of passive observations assumed in the *CloudSat* and CCP configurations.

Observing systems	Microwave Tb		VIS + near-IR imaging
	Measurement uncertainty	Total uncertainty	
<i>CloudSat</i> W band	4 to 5 K absolute uncertainty or 1 K cloud–clear relative uncertainty	Determined by the measurement uncertainty and also retrieval uncertainties that scale with LWP (Lebsock and Suzuki 2016)	5% uncertainty
CCP W + Ka band	0.5 K uncertainty		5% uncertainty

cross sections (Bohren and Huffman 1983) as a function of particle size. A detailed introduction of the radar forward model was offered in Posselt and Mace (2014). We implemented the algorithm using the time-dependent two-stream approximation (Hogan and Battaglia 2008) in the radar forward model to account for wide-angle multiple scattering. It is found the effect of multiple scattering is negligible for our cases, for which there was at most light precipitation. Accordingly, multiple scattering was turned off for computational efficiency in these experiments. PIA is estimated by integrating the extinction due to clouds and precipitation over the water paths (Haynes et al. 2009) with gaseous extinction due to oxygen and water vapor accounted for.

To simulate the required passive measurables (Tb and R), we adopted the forward models following Posselt et al. (2017). Radiative properties are derived using Mie theory. Visible and near-infrared radiances are computed with the Radiant model (Christi and Gabriel 2003), which is a multistream plane-parallel radiative transfer model that accounts for multiple scattering. The computation of passive brightness temperatures is based on a two-stream Eddington approximation (Kummerow 1993) and conducted with the model modified by Lebsock and Suzuki (2016). In the experiments that assume a CCP-like configuration, microwave model output is absolute Tb, while cloudy–clear difference is utilized in the A-Train configuration to reflect the vicarious calibration used for the *CloudSat* Tb estimates. Since our experiments utilize synthetic data that are generated from in situ data

collected over ocean, the solar zenith angle is set to 45° for simplicity. The surface albedo is set to 0.0644 and 0.153 for 0.55 and 2.1 μm reflectances, respectively. In our retrievals, the ocean surface wind speed is set to zero in the calculations of microwave Tb to be consistent with the assumption utilized in generating the synthetic observational profiles. Wind roughens the ocean surface, which in turn affects emissivity along with sea foam. Its influence on surface emissivity could become important when the wind speed exceeds 7 m s^{-1} (Meissner and Wentz 2012). Wind speed measurements or reanalysis data will be used as forward model inputs in the next-stage studies where the algorithm is applied to actual airborne and satellite remote sensing observations.

4. Results

a. Additional constraints from Ka-band measurements

A major step forward from the current *CloudSat* toward planning the CCP observing system is the possible addition of active and passive measurements operating at Ka-band frequency ($\sim 34.9 \text{ GHz}$, 8.6 mm wavelength). Note that, not only profiling radar and perhaps Doppler measurements, but also dual-frequency brightness temperatures and PIA become available with the addition of a Ka-band radar. Other differences between the two configurations include a more sensitive W-band cloud radar and Tb measurements with significantly higher precision in CCP (Table 1). The uncertainty of reflectance can be large

TABLE 2. Uncertainties of radar systems assumed in the *CloudSat* and CCP configurations.

Observing systems	Radar					
	PRF (Hz)	Integration time (s)	Minimum detectable reflectivity	Instrument noise	Reflectivity total uncertainty	PIA uncertainty
<i>CloudSat</i> W band	4300	0.16	−30 dBZ (W band)	1 dB	Depends on the radar	Depends on the
CCP W + Ka band	7000	0.1	−35 dBZ (W band), −10 dBZ (Ka band)		PRF, integration time, instrument noise, and scale with signal noise ratio above the minimum detectable reflectivity	radar system, and scale with LWP (Lebsock and Suzuki 2016)

FIG. 4. The posterior sampling space of a prior-only MCMC experiment with the RICO 0107 case, which maps the scene-consistent prior assumed in the retrievals. (a) Panels on the diagonal from top to bottom, respectively, show the one-dimensional histograms of rain mode liquid water content (g cm^{-3}), number concentration (cm^{-3}), and effective radius (μm). Off-diagonal panels show the two-dimensional joint probability density plots, where the filled contours correspond to 99%, 95%, 68%, 38%, and 12% probability, respectively. (b) As in (a), but for cloud mode variables. Note all the variables are plotted on a log base 10 scale.

($\sim 25\%$, e.g., in broken-cloud scenes), under which circumstances the constraints provided in synergistic retrievals that include radar and microwave radiometer data appear negligible (Posselt et al. 2017). Recognizing that a 25% uncertainty estimate represents an extreme upper bound, we set reflectance uncertainties to 5% in all of our experiments. This represents a slight increase over the 2% uncertainty assumed in the MODIS effective radius retrieval (S. Platnick 2018, personal communication) to account for three-dimensional radiative transfer effects.

As introduced in section 3, the MCMC algorithm samples the joint posterior probability distributions for the retrieved rain and cloud PSD parameters at each cloudy level. LWC, total number concentration, and effective radius are then computed to provide a more physical perspective. Figure 5 presents the retrieval solution space of the cloud and rain modes at 350 m below cloud top (i.e., the second level from cloud top). To illustrate the algorithm performance, we overlie the observational profiles (blue solid lines in Fig. 5) as well as the lower and upper 1σ standard deviation of the prior distribution (red dashed lines) on the one-dimensional histograms of retrieved variables. For both IPHEX 0512 and RICO 0114, the mode of light rain LWC_p , $N_{d,p}$, and $r_{e,p}$ in the solution space lines up well with the “true” in the experiments assuming the CCP configuration. The tendency is clearly present that posterior probability distributions

are driven by the observations toward the “true” from the prior, despite slight disagreements between the most likely solution and the “true” for some variables. In the *CloudSat* as well as CCP experiments, rain mode microphysical variables are significantly better constrained by observations than those of the cloud mode. The dispersions of cloud mode solution space remain comparable with the prior and no evident correlations exist in the two-dimensional joint probability distributions, while the mode of retrievals is in tune with observational profiles. In contrast, the retrieval space of rain mode variables is apparently narrowed from the scene-consistent prior, among which LWC_p is well constrained in both configurations.

Upgrading the *CloudSat* to CCP observing system, substantial improvements are exhibited primarily with respect to the rain number concentration and effective radius (Fig. 5). Meanwhile, ambiguities regarding the correlations among the rain variables are diminishing with the additional constraints afforded by Ka-band measurements. For instance, the retrieved rain mode $r_{e,p}$ is likely to increase with LWC_p when its value exceeds $250 \mu\text{m}$ (~ 2.4 in log base 10 in Fig. 5), while the sign of the correlation becomes negative when $r_{e,p}$ is smaller than $250 \mu\text{m}$ in the *CloudSat* experiment. On the contrary, a monotonic relationship is shown between $r_{e,p}$ and LWC_p in the CCP experiment, in accordance with the more restricted solution space. Similar improvements are also seen in the

RICO 0114

FIG. 5. (a),(b) As in Fig. 4, but for the posterior solution space of the second cloudy layer from top in the RICO 0114 case where the CCP configuration is assumed. Blue solid lines indicate the observational profiles, and red dash lines indicate the upper and lower 1σ standard deviation of the prior. (c),(d) As in (a),(b), but for the experiment assuming the *CloudSat* configuration. Note all the variables are plotted on a log base 10 scale.

IPHEX 0512 case (not shown). Not surprisingly, CCP outperforms the *CloudSat* observing system consistently through the cloudy column, regarding rain mode effective radius and R in particular.

The main findings are similar for the two cases, and therefore we present the 5%, 25%, 75%, and 95% quantiles as well as the mean and median of the retrieved vertical profiles for IPHEX 0512 only. As seen in Fig. 6b, a greater number of outliers are generated in the *CloudSat* experiment, where the 95% quantile of $r_{e,p}$ exceeds $800\ \mu\text{m}$ at the cloud bottom, while the “true” is

merely $350\ \mu\text{m}$. In the CCP experiment (Fig. 6a), 95% of the posterior samplings have rain mode effective radius tightly constrained below $400\ \mu\text{m}$, which is likely due to the information provided by the dual-frequency radars, given the considerable sensitivity of radar reflectivities to the droplet size. In terms of rain rates, similar contrast is also observed between the two configurations. In addition, various degrees of skewness are associated with the derived probability distributions for most presented variables. The cloud $r_{e,c}$ and R are positively skewed, while the cloud LWC_c tends to be negatively skewed.

IPHEX 0512

FIG. 6. (a) (from left to right) The statistics of the retrieved rain rates, rain effective radius, cloud number concentration, and cloud effective radius in the MCMC experiment assuming the ACE configuration for the IPHEX 0512 case. Each plot contains the mean (blue solid line), median (red solid line), 5th (green solid line), 25th (green dash line), 75th (yellow dash line), 95th (yellow solid line) percentiles, and the observational profiles (black solid line). Rain and cloud effective radius (μm) are plotted on a linear scale and other variables are on a log scale. (b) As in (a), but for the results generated in the MCMC experiment assuming the *CloudSat* configuration.

Standard deviation is commonly employed as a statistical measure of retrieval uncertainties. When the retrieval space is highly nonsymmetric, interquartile range (IQR) is instead considered to be a more robust quantification of uncertainties, which is defined as the difference between 75th and 25th percentiles (Wilks 2011).

The vertical profiles of IQR for both cases are depicted in Fig. 7. For the rain mode, the IQR of effective radius is mostly situated close to $60\mu\text{m}$ in CCP, while its value is markedly higher in the *CloudSat* configuration, with the maximum reaching approximately $250\mu\text{m}$. Notable contributions from the additional Ka-band measurements are also present in the profiles of rain rates. On the other hand, the differences regarding the vertically resolved cloud mode variables between the examined observing systems are much less significant. As expected, the retrieval uncertainties of cloud N_{dc} and r_{ec} appear smaller in CCP for RICO 0114. Nevertheless, there are slightly lower IQR at some cloudy levels in *CloudSat* for the other case. Likely causes may be twofold. First, such minute magnitude of

differences can be predominantly driven by the noise arising from the various assumptions in the retrievals rather than a robust signal that indicates the information contained in one observing system surpasses the other. As pointed out in Mace et al. (2016), significant averaging of similar profiles may be required to infer information regarding cloud-mode properties with statistical significance in the presence of a rain mode. Second, the analysis above centers on the inferred profiles of cloud properties, despite that radar observations are the single source for the vertically resolved information. Radar signatures in both frequencies are nearly equally dominated by the larger precipitation droplets in these cases with precipitation. As for the other measurements utilized, Tb and PIA offer integral constraints, and the contribution from reflectance is likely to decline with the increase of optical depth.

Next we examine the mass-weighted column variables computed from the retrieved vertical profiles. In comparison with the mean, the median is mostly found to more accurately represent the center of the

FIG. 7. (a) Profiles of the IQR for the (top left) rain rates, (top right) rain effective radius, (bottom left) cloud number concentration, and (bottom right) cloud effective radius for the IPHEX 0512 case. Red and blue lines indicate the CCP and *CloudSat* configurations, respectively. The black lines represent the observational profiles. Rain and cloud effective radius (μm) are plotted on a linear scale and other variables are on a log scale. (b) As in (a), but for the RICO 0114 case.

posterior probability distributions. Hence the discussion proceeds with the median fractional bias and IQR scaled by the “true” (Fig. 8). The former indicates how close the optimal solution is to the “true,” and the latter quantifies the retrieval uncertainties. In addition to the *CloudSat* and CCP experiments, the retrieval outcomes of three other MCMC experiments are exhibited in Fig. 8, which are (i) the same configuration as CCP but without the visible and near-IR reflectance in MCMC runs, (ii) an identical configuration as *CloudSat* but assumes a 0.5-K absolute uncertainty for Tb measurements, and (iii) increase the Tb uncertainty in (ii) to 5 K.

The column variables inferred within the *CloudSat* and CCP configurations are collated at the outset. In the IPHEX 0512 case, the scaled IQR of $r_{e,p}$ and R decreases by a factor of 3, as the configuration is switched to CCP (Fig. 8b). Concurrently, the scaled IQR of the rain mode LWP decreases by 40%. As for RICO 0114, the magnitude of disparity regarding $r_{e,p}$ is matching (about a factor of 3.5), in concert with less striking but still significant reduction in rain rates

IQR (Fig. 9b). In terms of the median, most notable reductions of fractional bias are present in the retrieved R . The median fractional bias of rain mode LWP reduces from 0.069 in *CloudSat* to 0.023 in CCP for IPHEX 0512, and similar magnitude of difference is also observed in RICO 0114. The cases consistently reveal that pronounced constraints are offered by the addition of the Ka-band radar reflectivity in conjunction with passive Tb and PIA measurements on the rain mode properties, which give rise to the median with enhanced accuracy and dramatically decreased retrieval uncertainties in the CCP experiments.

Regarding the cloud mode quantities in the precipitating cases, we find that the CCP observing system provides slight improvement in retrieving the cloud-mode LWP over what is possible with the A-Train observing system. This slight improvement in retrieved cloud LWP with the addition of the additional microwave active and passive frequency likely is realized by the improved information regarding the precipitation mode that then allows for a more accurate partitioning of the column-integrated Tb between cloud and

FIG. 8. (a) (from left to right) The median fractional bias of the retrieved liquid water path, cloud LWP, rain LWP, cloud number concentration, cloud effective radius, rain effective radius, and rain rates for five MCMC experiments with the IPHEX 0512 case, which are CCP without reflectance (green), CCP (orange), *CloudSat* (blue), *CloudSat* assuming 5-K absolute Tb measurement precision, and *CloudSat* assuming 5-K absolute Tb measurement precision (light gray). The median fractional bias is defined as the observation-scaled absolute difference between the true and median. See details about the MCMC experiments in text. (b) As in (a), but for the IQR scaled by the observation.

precipitation droplet modes. We also note, however, that the CCP configuration provides negligible improvement in cloud-mode r_e or N_d . In the nonprecipitating case (RICO 0107), we find that the CCP configuration only provides slight benefit over A-Train in terms of LWP. This can be understood by realizing that the Ka band information becomes significant over W Band for precipitation droplets in excess of several hundred microns. The passive microwave Tb information is also redundant and the PIA is not strong enough to really contribute.

Cloud N_d in all cases is poorly constrained by all observing systems. This can be understood by realizing that N_d is essentially the zeroth moment of the droplet distribution. With the radar scattering scaling with the sixth moment of the PSD, and the microwave emissions as the third moment, only visible reflectance in a second-moment dependence comes close to the moment that determines N_d . Interestingly it is apparently better constrained in the IPHEX case than the RICO cases. The median fractional bias is about 0.55, and the scaled IQR is approximately 1.6 in IPHEX 0512 (Fig. 8). In contrast, the values of the same statistical measure regarding cloud N_d are nearly an order of magnitude larger than other microphysical variables within the RICO cases. A better agreement between the prior and the “true” in IPHEX 0512 is most likely responsible for the discrepancies presented, given the fact that the information contained in the current measurements is far from sufficient to constrain $N_{d,c}$. The mode of cloud

number concentration in the assumed prior probability distribution is approximately 200 cm^{-3} (Fig. 4). The mass-weighted column number concentration is 215.8 cm^{-3} in IPHEX 0512 and less than 100 cm^{-3} in both RICO cases, which well represents the characteristics of the respective datasets. The IPHEX data targeting shallow cumuli were collected offshore near North Carolina and tends to share similarities with clouds generated over land. The RICO data were sampled over the eastern Atlantic and the western Caribbean, which is a more pristine oceanic environment.

As seen above, if the information afforded by observations is lacking, then the retrieval results are in essence dictated by the prior assumptions. There is little that can be done from a physics perspective to overcome the issue of ill-constrained N_d , which is an unfortunate truth since most characterizations of the aerosol–cloud interaction problem are grounded on how changes to aerosol influence droplet numbers in clouds. Retrieving N_d from space with available technology will remain elusive regardless of the observing system employed.

b. The influence of Tb measurement uncertainty

Besides the genre and operating frequencies of instruments in an observing system, the measurement uncertainty also underpins the amount of information that can be obtained. In terms of implementation, it is deemed as one of the concerns that drive the cost and challenge the technical feasibility of an observing system. A set of MCMC runs are conducted with the Tb

FIG. 9. As in Fig. 8, but for the RICO 0114 case and the statistics regarding cloud number concentration are shown in the individual panels due to their different ranges in y axis.

measurement precision perturbed from 0.5 to 5 K in the configuration where the higher uncertainty matches the absolute precision of Tb from the *CloudSat* experiment (Lebsock and Suzuki 2016). One could also consider the higher Tb uncertainty to be due to, perhaps, NUBF issues that might occur when the cloud field heterogeneity is particularly significant relative to the horizontal resolution of the observations. They are, respectively, indicated as CS_Tb0p5K and CS_Tb5K in Fig. 8. The comparison of output is focused on the total LWP, since the 94-GHz brightness temperatures place constraints on the column-integrated condensate mass without the capability to differentiate rain and cloud.

For all the cases, the median fractional bias, as well as the scaled IQR of total LWP, decrease in the experiments with 0.5-K accuracy. RICO 0107, the non-precipitating case, is found to be most sensitive to the perturbation in Tb measurement precision, where the median fractional bias and the scaled IQR regarding the total LWP reduce, respectively, by a factor of 3.8 and 2. Recall the microwave Tb uncertainty ultimately applied in our algorithms is determined as a sum of the instrument error and the retrieval uncertainties, which are primarily induced by nonuniform beamfilling effects (Lebsock and Suzuki 2016). The former is fixed to be either 0.5 or 5 K, and the latter is allowed to increase

monotonically with LWP. The retrieval uncertainty governs the total Tb uncertainty when the instrument error is set to be 0.5 K, while its influence becomes negligible in our experiments as the measurement uncertainty is enlarged to 5 K. The values of LWP vary with the case, ranging from 143 g m^{-2} in RICO 0107 to 573.7 g m^{-2} in RICO 0114. Correspondingly, the minimum Tb retrieval uncertainty is realized in RICO 0107 and the maximum in RICO 0114. The identical perturbation in measurement precision causes the largest increase in the total Tb uncertainty ($\sim 3.9 \text{ K}$) and significant response in the retrieved variables within RICO 0107, which suggests the clouds scenes with low LWP may be most subject to the Tb measurement precision.

c. The information provided by the reflectance measurements

The bispectral passive reflectance has been utilized to infer cloud effective radius, LWP, and total number concentration, based on the principle that reflectance at visible wavelength is primarily sensitive to the cloud optical depth, and near-IR reflectance includes sensitivity to cloud effective radius (Nakajima and King 1990). An intrinsic limitation associated with the application of solar reflectance is their unavailability during nighttime. An issue worth considering is whether reflectance measurements provide unique information with the coexistence of dual-frequency radar reflectivities, brightness temperatures and PIA. Furthermore, how are the constraints afforded by reflectance subject to the uncertainties of various measurements in the observing system? First we attempt to distinguish the impact of reflectance by removing it from the control configuration CCP, where the Tb measurement uncertainty is 0.5 K and the uncertainty of radar instrument noise is 1 dB. Regarding the IQR and median fractional bias of retrieved $N_{d,c}$ and $r_{e,c}$, the overall differences between the CCP and CCP configuration without reflectance (CCP_noRefl in Figs. 8–10) are not significant. The most notable distinction can be seen in the cloud N_d in one of the cases with precipitation (i.e., RICO 0114), where it is not well constrained even in the optimal configuration (i.e., CCP). The message conveyed in this comparison is that the contribution from passive reflectances is minimal in the default CCP configuration.

Speculating that relatively high-accuracy CCP microwave measurements may provide enough information to compensate for the loss of reflectance, we perform a further round of MCMC experiments with the nonraining case, where PIA is excluded and the uncertainties of dual-frequency Tb and radar reflectivities are inflated. The

sole difference between these experiments is whether visible and near-IR reflectance is useful in the observing system. When the measurement uncertainty of Tb and radar instrument noise is assumed to be 2 K and 3 dB, respectively, a discernibly smaller IQR of cloud $r_{e,c}$ emerges when measurements of reflectance are present (Fig. 11a). The contrast between experiments with and without reflectance becomes increasingly evident as the Tb and radar reflectivity uncertainties grow. The growth of such uncertainties would be realized in cases where NUBF becomes significant, for instance. In the extreme case in which radar and Tb carry very little information (Fig. 11c), the difference of $N_{d,c}$ IQR near cloud top escalates to 100 cm^{-3} , which is a factor of 2.5 relative to the “true.” Also, the tendency is well captured that the constraint of reflectance on $r_{e,c}$ diminishes with depth in the clouds.

A similar examination is performed with RICO 0114 to explore the role of reflectances in a situation that includes the existence of precipitation (Fig. 12). The IQR of all the cloud variables increases marginally in both experiments with and without reflectance, as the constraints provided by radar and Tb loosen. In comparison with the nonraining case, the differences attributable to the use of reflectance are less detectable as we increase the uncertainties of radar reflectivity and Tb to 3 dB and 4 K in the observing system. Furthermore, the fractional uncertainties of $N_{d,c}$ and $r_{e,c}$ overall tend to increase from cloud top to bottom. The information contributed by reflectances is found to be limited to near cloud top in this case where optical depth is approximately 50 and light rain occurs through the cloudy column except for the bottom layer. The reflectance measurement indeed provides valuable constraint for cloud properties, while its absence may be compensated by other active and passive measurements with decent precision. For instance, we hypothesize that high quality visible and near-infrared depolarization lidar measurements may be a credible alternative to visible reflectances especially at night. This possibility is being investigated.

5. Summary and conclusions

The last decade witnessed the tremendous success of the A-Train observing system, owing in large part to the synergistic use of vertically resolved W-band radar, microwave Tb, lidar backscatter, and reflectance measurements collected along coordinated orbits. Despite the information provided by the suite of A-Train sensors, it has become clear that the single-frequency A-Train radar observations are not adequate to simultaneously constrain cloud and precipitation

FIG. 10. As in Fig. 8, but for the RICO 0107 case, and only the cloud mode LWP, number concentration, and effective radius are shown.

microphysics without ambiguities (Christensen et al. 2013; Mace et al. 2016). Such simultaneous constraint of cloud and precipitation properties is necessary to infer microphysical processes ongoing within clouds at the time of observation. Therefore, simultaneous characterization of cloud and precipitation properties are of central importance for many critical science questions that confront the observational and modeling communities in the next decade. For instance, aerosol indirect effects cannot be meaningfully addressed without taking into account co-occurring precipitation in clouds (e.g., Jing and Suzuki 2018). In planning for the satellite missions of the next decade, ESAS 2017 points to the need for more process-oriented observations, which suggests the need for a conjunction of active and passive sensors whose genres are similar to A-Train but operate at perhaps

dual frequencies and possibly also with Doppler velocities (Kollias et al. 2014; Burns et al. 2016).

This paper proposes an approach for trade studies to be used in planning for next-generation cloud and precipitation observing systems. We compare the information contained in the pixel-level measurements of existing A-Train, alongside a notional observing system with selected candidate measurements based on the CCP concept, where radars, multifrequency passive microwave and submillimeter radiometers are recommended. By pixel level we mean that issues such as nonuniform beamfilling (NUBF) of the observations are neglected and/or that the assumed uncertainties in the measurements already accounts for NUBF. The CCP observations are expected to advance our understanding that are essential for climate projection, such as moist processes and cloud feedback.

RICO 0107

No PIA, 3-dB radar reflectivity uncertainty and 2-K Tb uncertainty

No PIA, 3-dB radar reflectivity uncertainty and 4-K Tb uncertainty

No PIA, 6-dB radar reflectivity uncertainty and 8-K Tb uncertainty

FIG. 11. Profiles of the IQR scaled by observations for the (left) cloud liquid water content, (middle) cloud number concentration, and (right) cloud effective radius for the nonraining RICO 0107 case. The red lines indicate the MCMC experiment containing reflectance measurements, and the blue lines indicate the experiment containing no reflectance, given other measurements and assumptions consistent in one subplot. Perturbations of uncertainties are based on the CCP configuration where PIA is not used. (a) Both experiments with and without reflectance assume 3-dB radar instrument uncertainty and 2-K Tb measurement uncertainty. (b) Both assume 3-dB radar instrument uncertainty and 4-K Tb measurement uncertainty. (c) Both assume 6-dB radar instrument uncertainty and 8-K Tb measurement uncertainty.

FIG. 12. Profiles of the IQR scaled by observations for the (left) cloud number concentration and (right) cloud effective radius retrieved in the RICO 0114 case with light rain. The red lines indicate the MCMC experiment containing reflectance measurements, and the blue lines indicate the experiment containing no reflectance, given other measurements and assumptions consistent in one subplot. (a) The CCP configuration (red) vs the CCP configuration without reflectance (blue). (b) As in (a), but remove PIA measurements from the CCP configuration and increase the instrument uncertainty of radar and Tb measurement uncertainty to 3 dB and 4 K, respectively.

Besides being dual frequency (W and Ka band), the CCP configuration assumes more precise measurements of microwave brightness temperatures and a W-band radar with a lower detection threshold in this study. Furthermore, the impact of measurement uncertainties on the information that can be extracted is investigated using Tb as an example.

In terms of implementation, a Markov chain Monte Carlo methodology is used to retrieve the vertical profiles of co-occurring cloud and light rain properties in warm-top marine boundary layer clouds. Across the MCMC experiments, we utilize a relatively tightly bounded scene-consistent lognormal prior that fits reasonably well to the representative in situ data collected during IPHEX, RICO, and OLYMPLEX. Given the prior and observational information, the MCMC algorithm is capable of generating the complete joint posterior sampling space without relying upon the assumption of Gaussian statistics, as is necessary in optimal estimation methods. It is found that the posterior probability distributions commonly exhibit non-symmetric features, under which circumstances the median mostly serves as a more representative measure of the optimal solution, as compared with the mean. Also, it provides quantification of information contained in measurements and allows the sensitivities of retrieval results to assumptions to be examined with rigor.

The primary purpose of the present study is to illustrate a methodology for assessing the measurement trade space that weighs complexity and capability against

cost and risk. The three cases illustrated, while representative of the life cycle of warm shallow cumulus, hardly represent an exhaustive spectrum. Certainly many more such cases will need to be considered for this cloud genre alone and similar studies will need to be conducted for other cloud and aerosol objectives. However, the three cases examined allow us to make several general observations. Our main findings are as follows:

- 1) In comparison with *CloudSat*, the uncertainty of $r_{e,p}$ and rain rates are conspicuously reduced in the raining cases with the incorporation of Ka-band radar reflectivity, brightness temperature, and PIA in the CCP configuration. Meanwhile, the ambiguities in the correlations between rain mode variables diminish. The information regarding the differential attenuation that emerges with the combined use of dual-frequency radars certainly further constrains the dependence of PSD moments on size in these cases with light rain (up to 37 mm day^{-1}).
- 2) Microwave brightness temperatures provide important constraints on the integral condensate mass in the cloudy column. Consider that Tb uncertainty assumed in the algorithms is a total of measurement precision and retrieval uncertainties (e.g., non-uniform beamfilling). In the CCP observing system with highly accurate Tb ($\sim 0.5 \text{ K}$), retrieval uncertainties are the dominant source in the total uncertainty. Otherwise, the measurement uncertainty tends to be the driving part. Retrievals for cloud

scenes with small LWP appear more sensitive to the choice of Tb measurement precision, ascribed to the fact that retrieval uncertainties are commensurate with the value of LWP.

- 3) The contribution from visible and near-IR reflectances is investigated, with their uncertainties consistently set to be 5% (Platnick et al. 2017) in the MCMC experiments. In the case without precipitation, the constraints on $r_{e,c}$ afforded by reflectances are primarily limited to the upper portions of the cloud layers and the constraints on $N_{d,c}$ could penetrate deeper into clouds. The impact of reflectances on all the examined cloud properties become more significant in the observing system where the amount of information from radar and Tb measurements is restricted due to enlarged uncertainties that may arise due to NUBF or other forward modeling errors. In the raining case, the influence exerted by reflectances is present, while it solely shows in the uppermost 350 m of the cloud.
- 4) It remains a challenge, even with the CCP configuration, to simultaneously derive the cloud properties with the occurrence of precipitation. Rain properties are overall far better constrained than the cloud mode microphysics, among which $N_{d,c}$ is most ill constrained even in the optimal CCP configuration although prior information more aligned with the specific cloud environments would likely somewhat ameliorate this issue. The observed contrast in terms of retrieved $N_{d,c}$ between the IPHEX and RICO cases very likely results from a better agreement between the assumed prior PDFs and the IPHEX case.
- 5) With limited sensitivities to available observations in certain moments of the droplet PSDs ($N_{d,c}$, for instance), retrieval outcomes heavily rely on the priors used in algorithms. Therefore, continuous observational efforts are called for to build extensive datasets, which will render a priori knowledge more faithful to nature and result in retrievals outcomes that can more faithfully address science questions. In other words, the capacity of an observing system to faithfully characterize the geophysical properties in nature is not only determined by the observing system characteristics but by the quality and scope of the prior statistics (variances and covariances of the geophysical parameters) that are to be retrieved.

In contrast to the currently operational GPM mission that employs Ku-/Ka-band radar and passive microwave observations that target precipitation in the low and midlatitudes (e.g., Hou et al. 2014; Grecu et al. 2011), a measurement system that employs a joint W- and Ka-band radar with sensitivities in the -30 and -10 dBZ

range, respectively, would be capable of probing much lighter precipitation as well as providing limited process-level information regarding cloud-to-rain conversion. The diagnosis of ice microphysical processes would also benefit from this combination of frequencies (Mace and Benson 2017). Meanwhile, the relatively small footprints are likely to mitigate some practical issues like nonuniform beamfilling and multiple scattering. On the other hand, limitations do exist even for the observing system envisioned herein. For instance, W-band radar measurements suffer severe attenuation when rain intensity is greater than 5 mm h^{-1} (Tian et al. 2007).

As the community begins considering potential observing systems to address the imperatives of the 2017 ESAS within the budgetary realities of modern times, the methodology presented here paves the way for an assessment approach that can provide rigorous expectations on what various measurement architectures can achieve. In addition, such assessment methodologies can point to shortcomings in our understanding and identify where our global observational statistics (i.e., a priori covariances) that are required to fully exploit investments in remote sensing systems must be augmented. Our ongoing efforts will allow us to extend the scope of the study by incorporating other hydrometeor types such as the ice phase and by expanding the realism of the forward models by accounting for multiple scattering, etc. Additional measurables will also be considered such as Doppler velocity so that retrievals of vertical air motions can be assessed.

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