Chapter 19

Cloud Property Retrievals in the ARM Program

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1. Introduction

Cloud feedbacks and processes have been clearly highlighted as a leading source of uncertainty for understanding global climate sensitivity (IPCC 2007). Clouds play fundamental and complex roles in the climate system by redistributing heat and moisture through modulation of atmospheric radiation, latent heating processes, and serving as a critical link in the hydrological cycle. They are affected by aerosol properties, large-scale circulation patterns, interactions with the surface, and tropospheric thermodynamic structure. Importantly, cloud systems are entwined in many feedbacks acting on both large and small scales (Stephens 2005). At the crux of the significant uncertainty associated with cloud processes is the fact that all of these properties, processes, and interactions of clouds with the earth's climate system vary widely across the globe leading to a diversity, variability, and complexity of cloud systems that is difficult to represent using numerical models.

Reaching climate equilibrium after some perturbation to the system can take decades of model simulated time; however, Gregory and Webb (2008) and Andrews and Forster (2008) found that changes in clouds that are typically attributed to feedbacks (i.e., Soden et al. 2004; Dufresne and Bony 2008) are actually realized rapidly after a sudden CO_2 doubling. These findings are consistent with Williams and Tselioudis (2007) who show that much of the disparity between models and observations is because models fail to represent clouds accurately within present-day meteorological regimes. This distinction is important because feedbacks are largely beyond the reach of observations. However, a rapid response by clouds to altered meteorological regimes suggests that much of the uncertainty in what is normally termed cloud feedbacks arises because of differences in how the parameterized macro- and microphysical properties of clouds respond to changes locally. This further implies that improved understanding of the interactions between cloud processes and the broader climate system in the present climate can have a direct bearing on the fidelity of climate change predictions if that understanding can be encoded in models.

Thus, understanding cloud systems at a physical process level is critical to advancing numerical earth system modeling abilities. Such a need for process level understanding is becoming increasingly important as numerical models move to finer and finer spatial scales. It is not unreasonable to assume that global

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cloud resolving models (Satoh et al. 2008) will be the preferred modeling tools in the future. As convective parameterizations are abandoned in favor of explicit microphysical parameterizations, it is the microphysical parameterizations that are increasingly being recognized as the weak link (Bryan and Morrison 2012; Han et al. 2013). Advancing numerical earth system modeling abilities requires tackling the complexities of clouds, including the following:

- formation processes and particle nucleation;
- transfer of water among three phases;
- evolution of particle size distributions related to growth, autoconversion, dynamics, and entrainment;
- growth regimes that lead to cloud particles of different shapes, sizes, and fall speeds; and
- scattering and absorption of atmospheric radiation.

To date many of these processes have been difficult to unravel and describe with predictive skill because they are difficult to observe. Many processes, such as entrainment and cloud particle formation, are largely hidden from direct observational capabilities. Further, the dimensionality of the problem (i.e., complexity of cloud systems) is much greater than the available observational constraints. These deficiencies together call for dedicated efforts to expand and improve cloud observational abilities in the form of new measurement technologies and sophisticated analytical tools that are better able to probe deeply into cloud processes and ultimately better constrain the cloud problem.

Over the past two decades, the U.S. Department of Energy (DOE) Atmospheric Radiation Measurement (ARM) Program (Stokes and Schwartz 1994; Ackerman and Stokes 2003) has taken a leading role in addressing the observational and modeling complexities of clouds. One foundational objective of the ARM Program has been to improve the representation of clouds in numerical models. To support this objective, the program has developed and operated diverse suites of ground-based cloud-sensing instrumentation at several geographically diverse locations. These efforts have produced publicly available cloud observational records that are historically unprecedented in length, continuity, and sophistication.

A major thrust of ARM's cloud activities has been in the development of cloud retrieval algorithms wherein instrument-level measurements are exploited to derive the geophysical properties of clouds that are needed to understand and represent cloud processes. These retrieval algorithms are a critical step in bridging the gap between basic measurements and model improvement. They provide input to observational and modeling process studies that are used to synthesize and generalize cloud knowledge in order to support model parameterization development.

Here we provide an historical overview of ARM's contributions toward cloud property retrievals. The overview covers advances in using specific passive and active instruments that are in operation at ARM sites and the expansion of multisensor retrieval approaches. It also addresses the general topic of uncertainty, how it is evaluated, and what it means for our ability to use cloud information derived from ground-based sensors. While there have been many individual contributions over the past two decades from investigators supported by ARM, the focus here is primarily on the larger movements and novel accomplishments that distinguish the ARM Program as a global leader in cloud research and retrieval development. We conclude with a look at the pathway forward, considering the possibilities presented by new enhanced measurements, the need to develop sophisticated forward models relating physical processes to observational parameters, and how these together can further advance cloud retrievals.

2. Cloud observing instruments

Since the early 1990s, the ARM Program has been a pioneer in designing and continuously operating ground-based atmospheric observatories. One strength of the ARM approach is the diverse, collocated, and complementary suites of well-characterized measurements that can be used individually and/or jointly to derive cloud properties in many atmospheric conditions. The value of this approach is that the diverse instruments provide measurements that constrain different aspects of cloud properties. In essence, the extreme dimensionality of the cloud problem can be made more tractable by using measurements that provide independent information about a cloudy volume or vertical column. Furthermore, by operating this instrument suite continuously, the ARM Program has been able to build datasets that extend over multiple years to characterize clouds in all seasons and conditions, and for accumulating the representative statistics needed for model development. In this regard, the ARM approach has been a model for other observational facilities around the globe (i.e., Haeffelin et al. 2005, 2016, chapter 29; Illingworth et al. 2007; Shupe et al. 2013).

Here we briefly summarize the basic set of instruments that compose the typical cloud-sensing component of each ARM site and serve as the data sources for cloud retrievals (see Table 19-1). More detailed information on all instruments is provided at www.arm.gov. These cloud-relevant sensors are characterized broadly into

TABLE 19-1. Core ARM cloud-sensing instrumentation available at most sites. Specific information on instrument specifications, operation parameters, deployment locations, periods of operation, data quality, and other relevant information are provided on the ARM web page at www.arm.gov.

Instrument	Measurements	Reference
Atmospheric Emitted Radiance Interferometer (AERI)	Spectral radiance, 3–25 μm	Knuteson et al. (2004a,b)
Ceilometer	Backscatter, 905 nm	—
Microwave Radiometer (MWR)	Brightness temperatures, 20–31, 90 GHz	Liljegren et al. (2001); Turner et al. (2007a)
Millimeter Cloud Radar (MMCR)	Reflectivity, Doppler spectra, Doppler moments, 35 GHz	Moran et al. (1998); Kollias et al. (2007)
W-band ARM Cloud Radar (WACR)	Reflectivity, Doppler spectra, Doppler moments, 95 GHz	Mead and Widener (2005)
Micropulse lidar (MPL)	Backscatter, depolarization ratio, 523 nm	Spinhirne (1993); Campbell et al. (2002)
Raman lidar	Backscatter and depolarization ratio, 355, 387, and 408 nm	Goldsmith et al. (1998); Turner et al. (2016, chapter 18)
Radiosondes	Temperature, humidity, winds	—
MFRSR family	Irradiance at multiple channels between 415 and 940 nm	Harrison et al. (1994)
Hemispheric Broadband pyranometer and pyrgeometer	Broadband irradiance, 0.3–3 and 4–50 μm	Michalsky and Long (2016, chapter 16)

two groups: passive sensors, where radiation emitted by the atmosphere at different wavelengths is simply measured by the instrument; and active sensors, where the instrument transmits a signal to the atmosphere and measures its return. Active sensors include millimeter-wavelength radars that are sensitive to cloud-sized hydrometeors (see Kollias et al. 2016, chapter 17), and measure the total radar reflectivity, as well as Doppler information on particle and air motions. Recent advances have allowed for measurement of the full radar Doppler spectrum as well. ARM radars include the Millimeter Cloud Radar (MMCR) and the W-band ARM Cloud Radar (WACR), in addition to recent upgrades and modifications to these systems to improve robustness and allow for scanning (Mather and Voyles 2013). Lidars that operate at visible or near-visible wavelengths (e.g., Campbell et al. 2002; Turner et al. 2016, chapter 18) are also critically important as they measure backscatter and depolarization ratio, which together contain information on cloud optical properties, particle shape, and hydrometeor phase, among others. ARM lidars include the Micropulse lidar (MPL), Raman lidar, and more recently the High Spectral Resolution lidar (HSRL). Each ARM site also includes a laser ceilometer, which operates on principles similar to the lidars.

Passive measurements provide critical radiative constraints and signatures of many cloud properties, thus ARM sites include passive instruments operating at a variety of targeted wavelengths. Microwave radiometers measure downwelling atmospheric radiances in the 23–31-GHz range that are sensitive to the total precipitable water vapor and condensed liquid water path. Higher-frequency channels near 90 and 150 GHz are sometimes used for enhanced sensitivity in particularly dry conditions. Moving to shorter wavelengths, the ARM Program operates the Atmospheric Emitted Radiance Interferometer (AERI) to obtain spectral infrared radiances. Among other properties, these spectral measurements contain information on the optical and microphysical properties of optically thin clouds. At visible and near-infrared wavelengths, the Multifilter Rotating Shadowband Radiometer (MFRSR), and related radiometers, measure solar irradiance at multiple narrowband channels, which provide information on cloud optical properties. Last, hemispheric broadband radiometers operating in both solar and thermal infrared spectral ranges offer constraints on bulk cloud properties and a linkage between clouds and net surface radiation.

The ARM approach has been to use instrument technologies that can operate continuously over long periods of time to provide robust, long-term datasets. As a result, most of the cloud-relevant instruments initially deployed at ARM facilities used a fixed viewing-orientation, typically pointing vertically. The assumption with this ''column'' viewing perspective is that long-term statistical analyses provide an ample representation of regional processes. However, this may not be the case if there are nearby geographic features that can influence the cloud field. Recent improvements in scanning technologies and the operational robustness of scanning, cloud-sensing instruments have allowed ARM to integrate these capabilities into its observational suite (e.g., Mather and Voyles 2013). These new observations, in coordination with the long-term vertically pointing measurements, offer the ability to evaluate the representativeness and relative capabilities of these two observational approaches toward characterizing cloud properties and processes.

3. Advances in cloud retrievals

The long-term, comprehensive datasets obtained from the ARM sites have laid the foundation for a wealth of cloud retrieval development. In some cases, the retrieval development has fed back to instrument development activities, leading to new measurements that offer additional information to constrain cloud properties. While many of the fundamental instruments and analytical techniques predate the ARM Program, the program has contributed to significant advances along a number of pathways in instrument development and data analysis.

a. Passive sensor systems

Passive microwave measurements have long been used to derive properties of the atmosphere. Through its emphasis on long-term operational measurements, the ARM Program has contributed to specific advances in ensuring robust, automated calibration for these microwave measurements (Liljegren 2000). Additionally, several advances have been made in retrieval algorithms. ARM investigators expanded on traditional microwave retrieval methods, which initially relied on statistical representations of atmospheric vertical structure to relate measured microwave radiances to the geophysical parameters of interest, such as the cloud liquid water path (LWP). These statistical retrievals were further constrained using local meteorological conditions and an estimate of the cloud temperature derived from collocated measurements (Liljegren et al. 2001). Additionally, a bias-offset technique was developed to account for clear-sky LWP biases related to variability of local conditions (Turner et al. 2007a). These enhancements resulted in a significant decrease in LWP retrieval bias and spread under clear-sky conditions, the latter of which is a nominal estimate of retrieval uncertainty (see Fig. 19-1). LWP retrievals were further constrained and enhanced with the addition of a physical, iterative approach that incorporates a priori information on atmospheric temperature and water vapor profiles from contemporaneous radiosonde measurements, showing improvement under certain conditions and confirming the quality of the enhanced statistical approach (Marchand et al. 2003; Turner et al. 2007a). This programmatic focus on deriving LWP in all conditions, including for very thin and cold clouds (e.g., Turner et al. 2007b; Wang 2007), promoted the development and integration of higher-frequency microwave

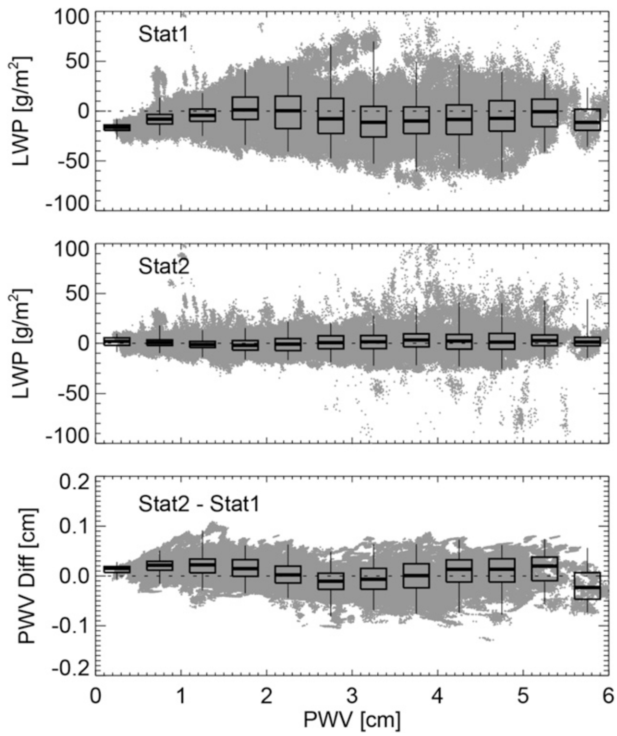

FIG. 19-1. Distribution of clear-sky liquid water path (LWP) from the Southern Great Plains site from September 1996 to December 2005, computed using the (top) original statistical method and the (middle) improved statistical method with brightness temperature offsets applied. (bottom) The difference in the retrieved precipitable water vapor (PWV) between the two methods is also shown. The box-and-whisker plots show the 25th and 75th percentiles (lower and upper boundaries of the box, respectively), the median value (thick line in the middle of the box), and the ends of the whiskers denote the first and ninety-ninth percentile points in the distribution. The size of each PWV bin is 0.5 cm. [Figure from Turner et al. (2007a), courtesy of *IEEE Transactions on Geoscience and Remote Sensing*.]

channels into LWP retrievals. The utility of the MWRs have forced the program to evaluate the accuracy of the underlying liquid water absorption models, which led to the conclusion that the initial liquid water absorption model used by the program had a large bias (Westwater et al. 2001) and that the current absorption model is inadequate in supercooled liquid water clouds (Cadeddu and Turner 2011; Kneifel et al. 2014).

The ARM Program has contributed to important advances in interpreting spectral infrared measurements from the AERI toward characterizing clouds. While infrared spectra contain information on the presence, concentration, and vertical profile of various gaseous constituents that are active in the thermal infrared, the microwindows between gaseous absorption lines can offer insight into the properties of clouds. Radiances in these microwindows have been used to derive the

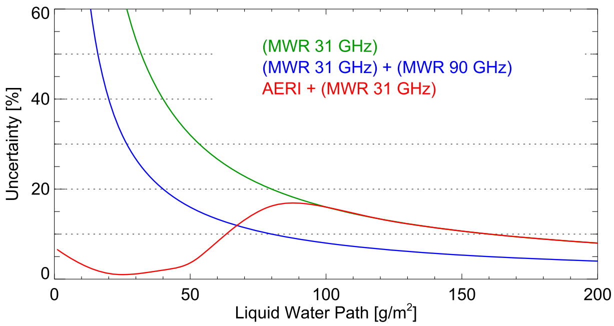

FIG. 19-2. Uncertainty in derived cloud liquid water path as a function of liquid water path for various combinations of measurements (microwave measurements at 31 and 90 GHz, and infrared measurements by the AERI) used in the retrieval process.

infrared cloud optical depth (DeSlover et al. 1999; Mitchell et al. 2006). Additionally, differential absorption of ice versus liquid water across the infrared spectrum has been exploited to determine cloud phase (Turner et al. 2003). Phase-dependent spectral microwindow signatures also form the basis for the retrieval of optical depth and hydrometeor effective radius of both liquid and ice components of mixed-phase clouds using a physically iterative optimal estimation approach (Turner 2005; Turner and Eloranta 2008). These retrievals can be performed only when the visible optical depth is greater than about 0.1 and less than about 6, such that the 8–13-μm band is semitransparent (i.e., not opaque) and, therefore, contains information on cloud properties. The high accuracy of AERI-based LWP retrievals in thin clouds has been combined with microwave radiometer-based LWP retrievals that perform better in thicker clouds to provide optimal retrievals over the full range of observed LWP (see Fig. 19-2; Turner 2007).

A variety of other passive retrievals for cloud optical depth using transmission of solar and near-IR radiation have been developed using ARM sensors, including: MFRSR (Min et al. 2004b; Min and Harrison 1996), broadband shortwave radiometers (Barnard and Long 2004), sun photometer (Marshak et al. 2004; Chiu et al. 2006), and oxygen A-band spectrometer (Min et al. 2004a). A technique for obtaining cloud optical depth in optically thick cirrus also was developed using the passive solar background signal from MPL systems (Chiu et al. 2007). This unique approach allows for the simultaneous retrieval of aerosol properties and cloud optical depth in broken low-level clouds.

b. Active sensor systems

Millimeter wavelength cloud radar has been an early centerpiece of the ARM approach, and ARM has contributed to significant advances in the development of operational, millimeter wavelength, cloud radars (e.g., Kollias et al. 2016, chapter 17). Prior operational radars were typically longer-wavelength precipitation-observing systems, while most prior cloud radar measurements were limited largely to a few, targeted campaigns using research-grade instruments that were not operated operationally. ARM's continuous radar operations in multiple locations have provided first-of-a-kind datasets that are fertile for radar-based cloud retrieval development.

These longer-term datasets have been used to better constrain the traditional radar power-law relationships that relate radar reflectivity Z to geophysical parameters such as the cloud ice water content (IWC) (e.g., Matrosov et al. 2003; Shupe et al. 2005) or liquid water content (LWC; e.g., Matrosov et al. 2004; Dunn et al. 2011). By capitalizing on cloud radar Doppler abilities and utilizing relationships between ice particle terminal fall speed, particle size, condensed mass, and backscatter cross section, information on ice crystal characteristic size and IWC can be derived simultaneously (e.g., Mace et al. 2002; Matrosov et al. 2002). Additionally, radar-based retrievals of cloud optical depth have even shown some potential in ice clouds (Matrosov et al. 2003).

Cloud radar-based retrievals of precipitation are another area in which the ARM Program has made important contributions. While typically derived using longer wavelength radars, the ability to retrieve precipitation properties from cloud radars allows for studies of the evolution and relation between clouds and precipitation properties above a single location. For snowfall rate S, the traditional reflectivity-based Z–S relationship formulation has been applied to millimeter-wavelength observations in dry snowfall, comparing to within a factor of 2 with independent snow gauge measurements (Matrosov et al. 2008). Such traditional reflectivity-based relationships are not possible for cloud radars operated in rain due to strong attenuation and non-Rayleigh scattering effects. However, these limitations have been capitalized upon by the development of attenuation-based retrievals for rainfall rate (Matrosov 2005; Matrosov et al. 2006) and raindrop size distribution retrievals using non-Rayleigh scattering signatures in radar Doppler spectra (Kollias et al. 2002, 2003; Giangrande et al. 2010).

The broader use of cloud radar Doppler spectra has been a game changer and is arguably the area in which ARM has made the largest and most distinctive contribution to cloud radar retrievals. In typical applications, only the first one to three moments of the Doppler spectrum are utilized in cloud retrievals. However, advances in computational power and data storage have allowed for the routine collection of the full Doppler

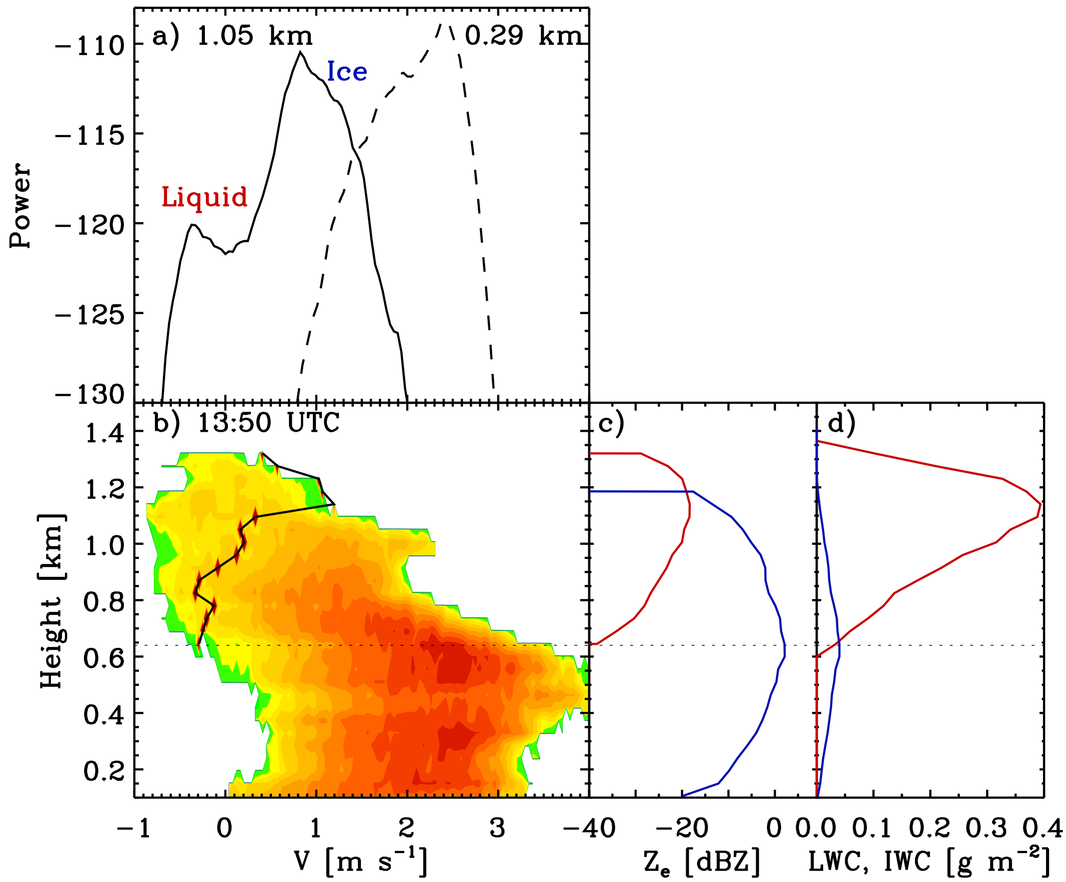

FIG. 19-3. Doppler spectrum analysis in stratiform mixed-phase cloud conditions. The Doppler spectrum is the distribution of returned radar power as a function of the radial velocity of the targets in the radar volume (positive velocity is downward). (a) A bimodal spectrum (solid) found in mixed-phase conditions near cloud top and a unimodal, ice-only spectrum (dashed) found below the liquid cloud base. These spectra are horizontal slices through the spectrograph in (b), which shows contours of returned power as a function of velocity and altitude (redder colors indicate higher power). A manually determined line distinguishes the liquid and ice phases in the spectrograph. (c) Based on the distinction of phase contributions to the spectrograph, individual profiles of liquid (red) and ice (blue) reflectivity, which are the total power in each mode, are computed. (d) Example profiles of liquid (red) and ice (blue) water contents derived from the distinct liquid and ice radar reflectivity profiles. [Figure from Shupe et al. (2008a), courtesy of the *Bulletin of the American Meteorological Society*.]

spectrum, unlocking a wealth of new information. Full spectra often contain multiple modes and different shapes that have been used to identify the presence of supercooled liquid water layers in mixed-phase clouds (Luke et al. 2010). Further, these complex spectra can facilitate independent characterization of liquid and ice components in mixed-phase clouds (Fig. 19-3; Shupe et al. 2004, 2008a; Rambukkange et al. 2011) and the distinction of cloud droplet populations from drizzle (Luke and Kollias 2013). Higher-order spectral moments, such as skewness and kurtosis, have been harnessed to identify processes such as drizzle formation (Kollias et al. 2011; Luke and Kollias 2013) and form the basis for a higher-order-derived data product called the Microphysical–Active Remote Sensing of Cloud Layers (MICRO-ARSCL) that reveals a great deal of information on microphysical processes and spatial structure within cloud layers.

c. Combined sensor approaches

Multisensor cloud retrievals increase the dimensionality of the input information, and thereby provide a stronger constraint on complex, multidimensional cloud properties. Moreover, such retrievals harness the strength of ARM sites with their extensive suites of coordinated measurements. Since clouds occur over a wide range of microphysical conditions related to phase, shape, number concentration, and size, no single instrument is optimally specified to detect all cloud conditions. For example, radar backscatter signals are proportional to the particle size to the sixth power, while lidar backscatter signals are proportional to the particle size squared, making these two instruments sensitive to different moments of the hydrometeor size distribution. Thus, to even simply observe the fractional occurrence of clouds and their heights requires a combined sensor approach (e.g., Comstock et al. 2002; Shupe et al. 2011; Borg et al. 2011).

One of the first approaches for building combined remote sensor cloud climatologies of cloud presence was developed early on within ARM. The ARSCL (Clothiaux et al. 2000) product optimally combined information from collocated radar and lidar to identify the vertical locations of all cloud layers. This first-order cloud product has been a widely used cornerstone of the ARM Program, and has enabled many long-term studies for understanding basic properties, such as cloud overlap (Mace and Benson-Troth 2002), and for evaluating models. Furthermore, data products like ARSCL have enabled the ARM Program to continue to support other multisensor retrieval development.

Cloud phase is a critical detail for studying and understanding cloud processes and the interactions of clouds with the climate system. Additionally, identification of cloud phase is often a prerequisite to the application of cloud retrieval techniques, which are typically designed for a specific cloud type usually characterized by phase. The diverse collection of ARM measurements contains complementary, phase-specific signatures that can be used together to constrain cloud phase. Multisensor, threshold-based techniques have been developed for classifying clouds according to meteorological type (Wang and Sassen 2001) and phase type (Shupe 2007), the latter of which is specifically designed to inform retrieval algorithms. However, cloud processes are not always best quantified by discrete thresholds (i.e., phase transitions do not necessarily occur at specific temperatures or radar reflectivities), such that more flexible classification criteria might be warranted. To meet this challenge, a neural network–based classification approach was developed to recognize phase-specific patterns within cloud radar Doppler spectra based on a training dataset of depolarization lidar measurements (Luke et al. 2010).

Characterizing the microphysical properties of clouds is critical for understanding internal cloud processes and cloud impacts on radiation. Multisensor techniques have been developed using various combinations of ARM measurements to target the microphysical properties of specific cloud classes, often pairing an active measurement with an additional constraint offered by passive radiative measurements. For example, in thin, nonattenuating cirrus clouds the lidar-infrared radiometer (LIRAD) method joins lidar integrated backscatter coefficient with the IR absorption derived from passive radiances at 10–12 μm to derive cloud IR emittance and visible optical depth. This technique pioneered in the early 1970s (Platt 1973) has been applied to extended ARM datasets in the tropics (Comstock and Sassen 2001; Comstock et al. 2002). A similar combination of IR radiances with radar reflectivity in cirrus clouds (Mace et al. 1998; Matrosov 1999) has been used to derive both layer-averaged and vertically resolve estimates of IWC and particle characteristic size (e.g., Fig. 19-4).

For nondrizzling liquid water clouds, microwave measurements have been combined with broadband shortwave radiation to iteratively retrieve layer-mean cloud properties with the aid of a radiative transfer algorithm (Dong et al. 1997). Profile information on LWC and droplet effective size in this same type of clouds has been derived by pairing the profile information from radar reflectivity with the column constraint of microwave brightness temperatures (Frisch et al. 1995; McFarlane et al. 2002). Mace and Sassen (2000) combined the constraints provided by radar, passive microwave, and solar flux to examine the vertical properties of nondrizzling stratocumulus. Last, retrievals based on two active sensors also have been developed, wherein the different responses of lidar and radar backscatter to hydrometeor size have been exploited to derive information on particle size and other properties (Wang and Sassen 2002). Zhao et al. (2011) developed a method that combined the first two radar Doppler moments with information from a Raman lidar in a Bayesian algorithm to explore the bimodality of cirrus particle size distributions.

Mixed-phase clouds are difficult to characterize due to the presence of both liquid and ice hydrometeors in the same cloud layer. Attempts to meet this challenge have been made using unique applications of multisensor ARM data that take further advantage of the differential response of different instruments to the properties of cloud liquid and ice. For stratiform mixed-phase clouds, Wang et al. (2004) applied a combined radar–lidar method to characterize precipitating ice crystals, then used infrared radiances and an iterative-minimization approach to derive the cloud liquid water properties (e.g., Fig. 19-5). Others have used radar or radar-plus-lidar measurements to characterize the ice component and microwave radiometer to characterize the liquid component, in some cases implementing an assumption of adiabatic liquid water distribution (Shupe et al. 2006; de Boer et al. 2009).

A final class of multisensor retrievals is the combined sensor, all-cloud, all-condition retrieval suite that is designed for operational application to all observations made over extended time periods. Such suites not only rely upon multiple sensors but also combine a number of different cloud retrieval techniques that may be designed for specific conditions. ARM's initial movement toward

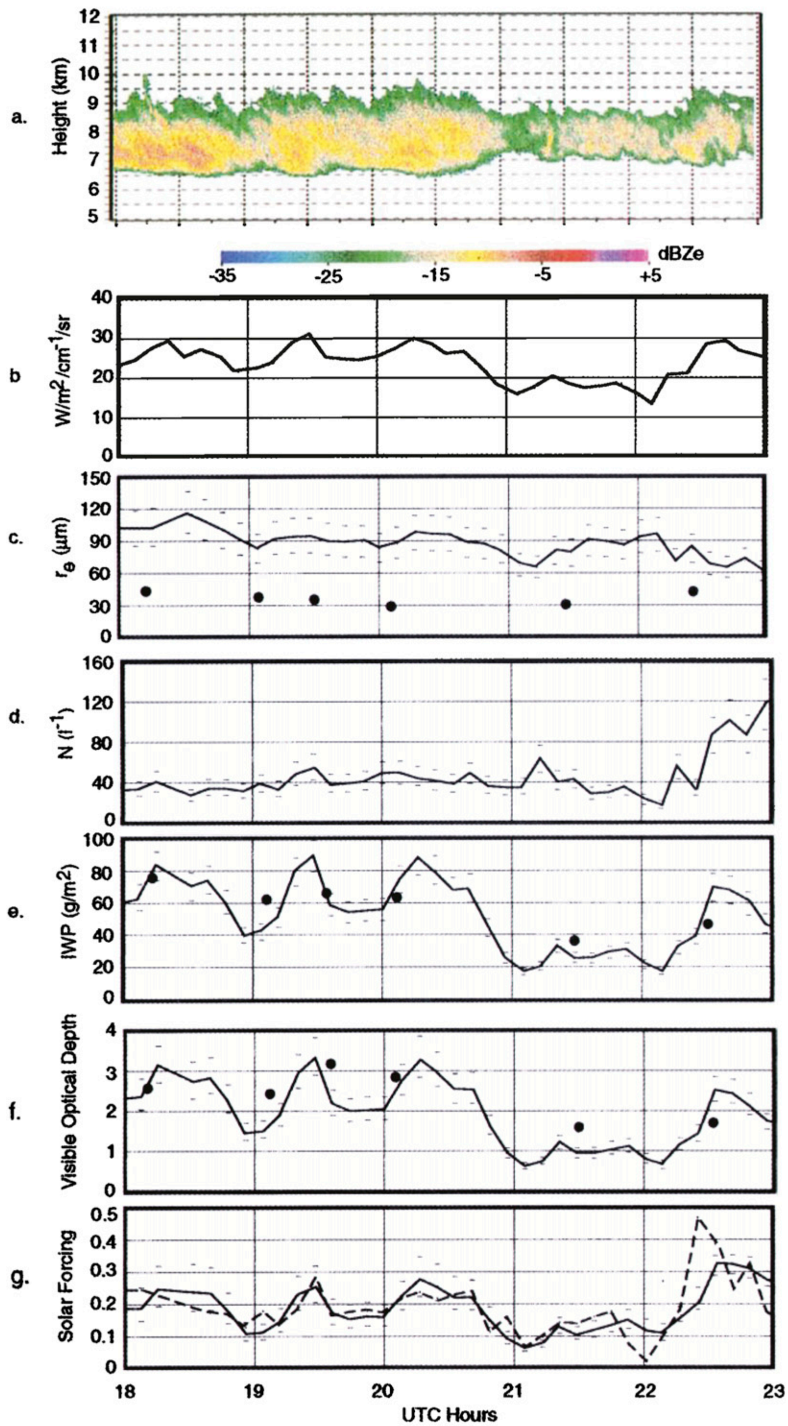

FIG. 19-4. Demonstration of radar reflectivity–infrared radiance retrieval of ice cloud properties for a case on 5 Apr 1996 at the Southern Great Plains site. (a) Time–height section of 94-GHz radar reflectivity, (b) 11-μm radiance from AERI, (c) retrieved effective radius, (d) retrieved particle concentration, (e) retrieved ice water path, (f) retrieved visible optical depth, and (g) comparison of the observed solar flux (dashed line) with the solar flux calculated using the retrieval results in (e) and (c). The flux is expressed as the fraction of the clear-sky flux removed by the cloud layer. (c)–(g) Solid lines show results from the radar-radiance algorithm, the horizontal tick marks show the uncertainty determined from the standard deviations of the radar reflectivity and AERI radiance, and the circles show results derived from geostationary satellite radiances. [Figure from Mace et al. (1998), courtesy of the *Journal of Geophysical Research*.]

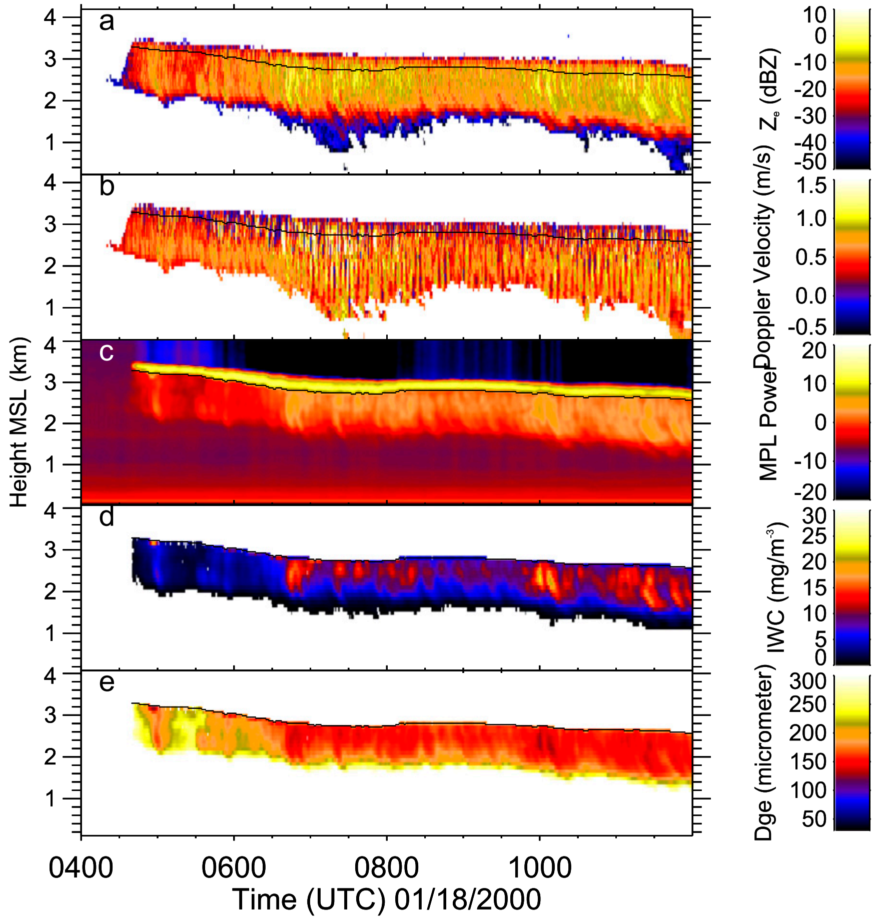

FIG. 19-5. Display of (a) radar reflectivity, (b) mean Doppler velocity, and (c) micropulse lidar return power, and the (d) retrieved ice water content and (e) effective diameter of ice virga on 18 Jan 2000 at the North Slope of Alaska site. Black lines in (a)–(c) denote the base of supercooled water cloud determined by lidar measurements. [Figure from Wang et al. (2004), courtesy of the *Journal of Applied Meteorology*.]

this type of operational retrieval was through the baseline cloud microphysics product called MICROBASE (Miller et al. 2003; Dunn et al. 2011), which applied a collection of simple yet widely applicable methods. Since that initial development, several other retrieval systems have been produced that implement more complex retrievals (e.g., Mace et al. 2006; Shupe et al. 2015; see Zhao et al. 2012 for a summary of others), often showing improved performance relative to certain metrics such as radiative closure at the surface.

d. Cloud-scale dynamics retrievals

In addition to deriving cloud macro- and microphysical properties, ARM has invested significant efforts toward observing and understanding the cloud-scale dynamics that impact cloud processes. Modeling groups both within and external to ARM have called repeatedly for enhanced information on vertical motions and turbulence within a variety of cloud types. To address this need in a concerted fashion, ARM developed the Vertical Velocity Focus group in the mid-2000s.

Since different cloud conditions have unique vertical motion characteristics and signatures, methods have been developed to specifically target distinct cloud types. Multiple retrievals have been developed for cirrus clouds, including an optimal estimation retrieval that uses the first three moments of the radar Doppler spectrum to jointly derive vertical velocity and cloud microphysical properties (Deng and Mace 2008) and a decomposition of radar Doppler velocities into reflectivity-weighted particle-fall velocities and vertical-air velocities using linear regressions between measured reflectivity and velocity at specific heights (see Fig. 19-6; Protat and Williams 2011; Kalesse and Kollias 2013). For low-level liquid clouds, the fact that cloud droplets trace air motions can be exploited to estimate vertical air velocity

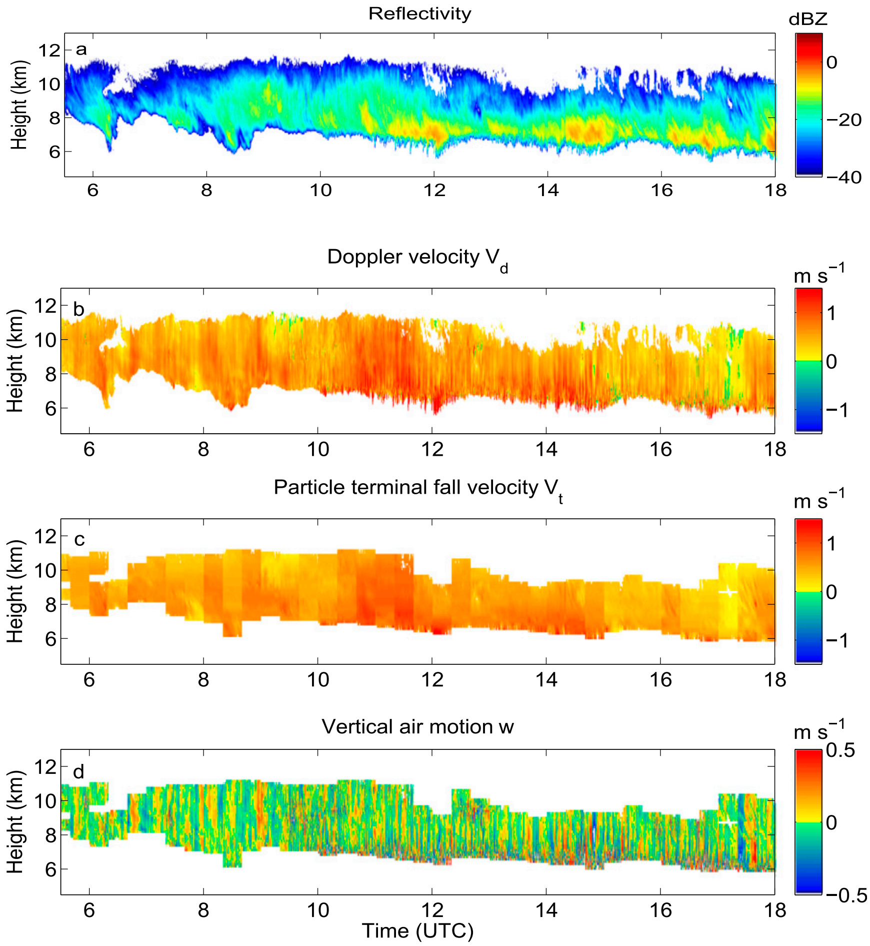

FIG. 19-6. Example of radar Doppler velocity decomposition into particle terminal fall velocity and vertical air motion on 8 Dec 2004 at the Southern Great Plains site. Positive velocity values indicate downward motion. (a) Radar reflectivity, (b) mean Doppler velocity, (c) particle fall speed, and (d) vertical air motion. [Figure from Kalesse and Kollias (2013), courtesy of the *Journal of Climate*.]

directly from radar Doppler velocities (Kollias et al. 2001; Ghate et al. 2011). This same basic principle also has been exploited in mixed-phase clouds, although full Doppler spectra are used to isolate the velocity signal from the liquid droplets (Shupe et al. 2008b). Vertical air motions in deep precipitating systems have been derived by using non-Rayleigh scattering signatures from large raindrops in cloud-radar Doppler spectra (Kollias et al. 2002, 2003; Giangrande et al. 2010). Finally, an estimation of the turbulent dissipation rate associated with cloud-scale dynamics has been adapted to high-temporal-resolution cloud radar velocity measurements (Shupe et al. 2008b, 2012).

4. Quantifying uncertainty and retrieval evaluation

Uncertainty quantification is an important component of any retrieval algorithm framework. Characterization of cloud retrieval accuracy is needed to understand the utility of retrieval results for conducting scientific process studies, developing model parameterizations, or addressing important climate questions. Several techniques for estimating and quantifying the uncertainty in retrieved cloud properties have been used extensively over the ARM Program's history, including algorithm intercomparisons, comparisons with aircraft in situ measurements, radiative closure studies, and more recently the use of optimal estimation techniques. All of these techniques face their own challenges and continue to be areas of active research and development toward improving retrieval uncertainty quantification.

a. Aircraft evaluation

In the early years of the ARM Program, several aircraft based field experiments were undertaken to sample cloud properties over the ARM Southern Great Plains

(SGP) site to help understand the radiative, dynamic, and microphysical properties of clouds. Modeled in part after the First International Satellite Cloud Climatology Project (ISCCP) Regional Experiment (FIRE) field programs of the late 1980s and early 1990s, which focused on satellite-based validation, these early ARM aircraft campaigns focused their efforts on supporting the growing ground-based Cloud and Radiation Testbed (CART) in the central plains of the United States. An important component of these early aircraft studies was to provide datasets for developing and evaluating ground-based retrievals of cloud properties and allowing a detailed look at cloud characteristics that are difficult to discern from remote sensors, such as droplet or ice crystal number concentration and size distribution, and bulk water content. The Subsonic Aircraft: Contrail and Cloud Effects Special Study (SUCCESS) campaign (Toon and Miake-Lye 1998), supported jointly by DOE ARM and NASA and the spring cloud intensive observing periods in 1998 and 2000, which focused on the properties of contrail cirrus, cirrus, and low-level liquid clouds (Dong et al. 2002), provided some of the first intercomparison datasets for ground-based remote sensors such as lidar and MMCR.

Subsequent field experiments tackled more complex cloud systems in different climatic regimes and clouds that are difficult to detect with single wavelength ground-based sensors. Arctic mixed-phase clouds present unique challenges for retrieval algorithms in that they require the simultaneous distinction between ice and liquid in the same volume. Aircraft measurements obtained during the Mixed-Phase Arctic Clouds Experiment (M-PACE; Verlinde et al. 2007) and the Indirect and Semi-Direct Aerosol Campaign (ISDAC; McFarquhar et al. 2011) were critical in helping interpret the radar Doppler spectra measurements and evaluating mixed-phase cloud retrievals. The Tropical Warm Pool–International Cloud Experiment (TWP-ICE) provided additional datasets in undersampled tropical cloud systems, and made progress in understanding the role of ice crystal shattering on aircraft-based probe inlets (McFarquhar et al. 2007).

An integral component of retrieval algorithm development is building a database of cloud properties measured in situ under various seasons and atmospheric conditions. ARM developed a unique approach to building these statistics using extended field campaigns. The Routine ARM Aerial Facility (AAF) Clouds with Low Liquid Water Depths (CLOWD) Optical Radiative Observations (RACORO; Vogelmann et al. 2012) aircraft campaign set out to document the statistical properties of tenuous liquid clouds in the boundary layer through routine measurements over a six-month period. Because of their thin optical depth, small droplet size, and often-small cloud fraction, low liquid water path clouds are difficult to detect with standard radiometric instruments, as well as cloud radar. Data obtained during RACORO helped develop the missing link in the characterization of these properties and provided the much needed evaluation dataset that helped develop the leading microwave and infrared radiometer retrievals. Likewise, the Small Particles In Cirrus (SPARTICUS) campaign accomplished a similar task as RACORO, but focused its efforts on cirrus clouds (Deng et al. 2013). The DOE ARM Program continues to be committed to building these important in situ datasets for retrieval algorithm development.

b. Algorithm intercomparisons and radiative closure techniques

As various datasets of cloud microphysical properties became available, there was a clear need to determine the sensitivity and accuracy of each algorithm and to begin assigning uncertainty to retrieved quantities. A pair of cloud retrieval algorithm intercomparisons examined retrievals of low-level, low LWP clouds (Turner et al. 2007b) and cirrus clouds (Comstock et al. 2007). Turner et al. (2007b) compared the LWP, effective radius (r_e), and optical depth of low LWP clouds derived from 18 different algorithms using different types of measurements (i.e., passive versus active sensors). Comparing retrieved cloud properties directly provides understanding of the spread (minimum/maximum) of the algorithms, but does not necessarily provide an independent measure of uncertainty. To help quantify the uncertainty, they used two forward model closure tests. First, the retrieved cloud properties were inserted into a radiative transfer model to compare computed surface shortwave diffuse fluxes with those observed using broadband radiometers. Second, the computed and observed cloud radar reflectivities were compared. These two different comparison methods independently tested the retrieved r_e and LWP. The main findings of Turner et al. (2007b) revealed that the large spread in the retrieved properties presents a continuing challenge for retrieval developers. This example, which focused on the simple case (single-layer, stratiform liquid clouds) also suggested that the measurements themselves require improved sensitivity or additional detection channels [i.e., the 90-GHz channel in the new 3-channel microwave radiometer; Cadeddu et al. (2013)] to improve the comparison with independent observations.

The cirrus community likewise examined a case study from the March 2000 cloud intensive observing period, where 14 different ice cloud retrieval algorithms were compared (Comstock et al. 2007). Independent satellite

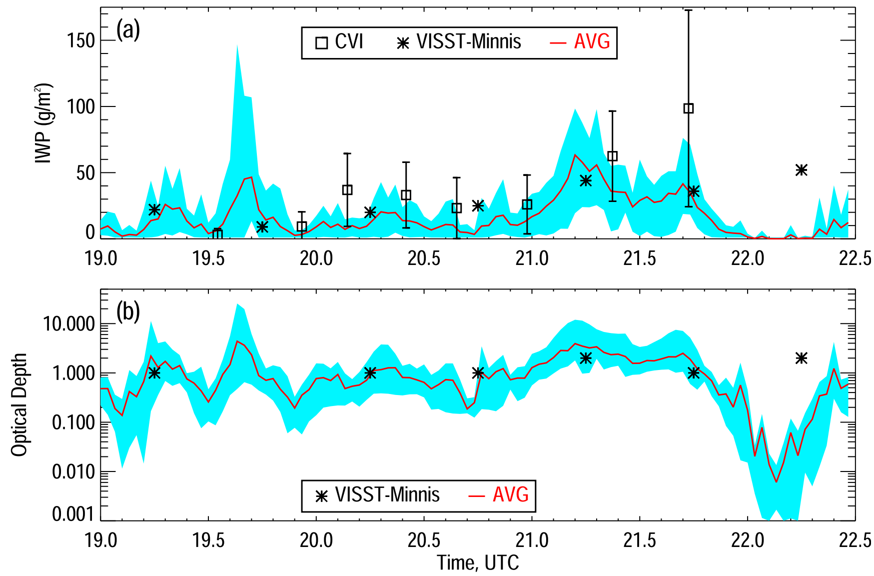

FIG. 19-7. Comparison of (a) ice water path and (b) optical depth derived from 14 different ice cloud retrieval algorithms. The blue shading represents the min and max and the solid red line indicates the mean for all retrievals. Results are compared to in situ (CVI; box) and satellite-derived (VISST-Minnis; asterisk) quantities. [Figure from Comstock et al. (2007), courtesy of the *Bulletin of the American Meteorological Society*.]

and aircraft-based measurements of ice water path (IWP) and visible optical depth τ were used to help evaluate the retrievals. The spread in the retrieved IWP was as large as 100 g m^{-2}, and sometimes larger than an order of magnitude in τ (Fig. 19-7). The mean IWP and τ compared reasonably well to satellite retrievals, although most retrievals underestimated IWP compared to in situ observations.

Similar to the Turner et al. (2007b) study, Comstock et al. (2007) also used radiative closure to determine the uncertainty in retrieved cloud properties. They compared computed surface downwelling shortwave flux with observations from broadband radiometers located at the SGP site. Their findings show that for optically thin cirrus ($\tau < 1$) the retrieved flux is typically smaller than the observed flux, suggesting that τ in thin clouds is overestimated. In contrast for $\tau > 1$, the mean retrieved flux is in better agreement with the observed flux (Comstock et al. 2007).

Clearly radiative closure is an important tool for evaluating retrieval algorithms; however, there are several assumptions that are inherent to the radiative transfer models. Assumptions regarding ice crystal shape, particle size distribution, surface albedo, and aerosol loading will all contribute to the uncertainty in these comparisons, but can also help identify specific aspects of retrievals where improvement is needed. The above-mentioned comparisons focused their efforts on single case studies. More recently, longer-term datasets were examined to further quantify the uncertainty in retrieved cloud properties. Several ARM-sponsored focus groups have helped champion these efforts. In particular, the CLOWD focus group compared passive infrared and microwave retrieval techniques using observations at the ARM mobile facility deployment at Pt. Reyes, California. This location provided an extensive dataset of low liquid water path, stratiform clouds for algorithm evaluation (Turner 2007). By examining the mean shortwave flux difference (Fig. 19-8, top) as a function of LWP, Turner (2007) found that both small (<30 g m^{-2}) and large (>60 g m^{-2}) LWP clouds produce large deviations from the observed fluxes. However, the two retrieval methods evaluated demonstrated that the AERI-based method resulted in significantly less scatter (as shown by the variance in the middle panel of Fig. 19-8) than the MWR-based method, and thus was deemed to be a more accurate retrieval even though both retrievals had approximately the same bias.

An additional long-term study compared cirrus cloud properties derived from radar and combined radar–lidar algorithms using three years of observations from the ARM site located in Darwin, Australia (Comstock et al. 2013). These comparisons focused on retrievals from active remote sensors that provide vertical profiles of cloud properties. Demonstrating another variation of radiative closure by examining the transmittance

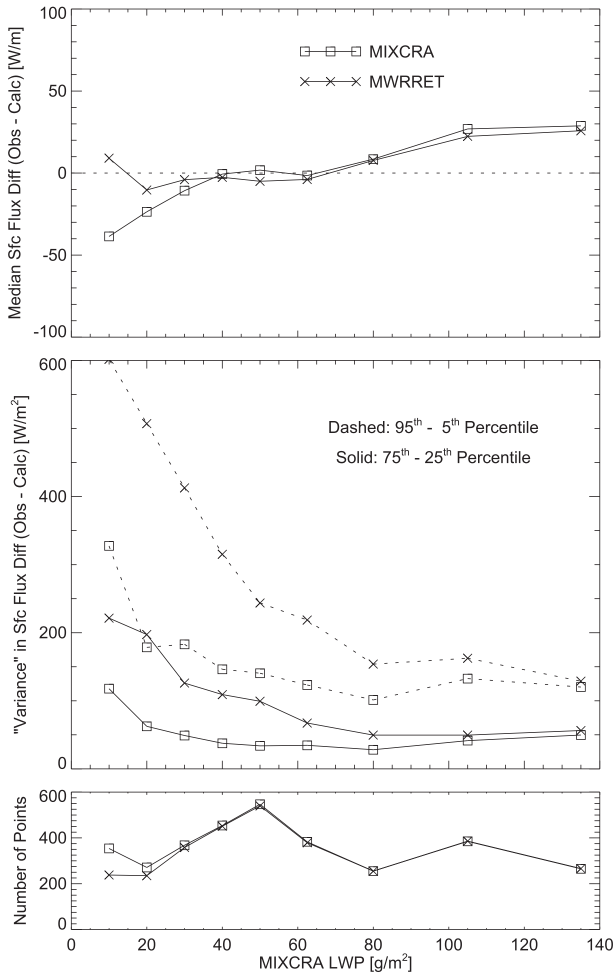

FIG. 19-8. Downwelling surface shortwave flux difference (observed − computed) as a function of cloud liquid water path. The median (top) and variance (middle) show the sources of uncertainty in liquid water path retrievals using the AERI-based MIXCRA method vs the microwave-based MWRRET method. (bottom) The number of points included in the analysis. [Figure from Turner (2007), courtesy of the *Journal of Geophysical Research*.]

difference (Fig. 19-9), Comstock et al. (2013) found that lidar–radar retrievals are generally less biased relative to the observed transmittance for clouds detected by both radar and lidar, as expected. The reflectivity–Doppler velocity (Z–V) algorithms also tend to be less biased but have larger variance. Primary differences between algorithms are related to the particle shape assumptions. Overall, the studies of Turner (2007) and Comstock et al. (2013) provide a basis for long-term evaluation of retrieval algorithms using the radiative closure approach.

However, radiative closure evaluation must also be used with care. For example, Protat et al. (2014) compared the long-term record of derived cloud properties and radiative forcing collected at the Darwin ARM site with similar estimates of cloud properties and radiative forcing derived from A-Train satellite measurements (Stephens et al. 2008). They found that, because of ubiquitous underlying cloud cover and sensitivity limitations of the ARM ground-based remote sensors, the majority of thin cirrus are not sensed by the ARM remote sensors. Conversely, they also document that the A-Train tends to miss a significant fraction of the low-level clouds. Each of these discrepancies results in unique biases with respect to cloud radiative effects. The ARM data at Darwin, because it misrepresents tropical cirrus, has a large heating rate and infrared radiative forcing biases in the upper troposphere, while the A-Train incorrectly characterizes the solar forcing due to boundary layer clouds. At the same time, another study by Thorsen et al. (2013) suggests that the bias in observing tropical cirrus might be much less when using ground-based Raman lidar. These studies highlight the potential difficulties of using radiative closure in assessing uncertainties in cloud property characterizations and emphasize the need for a critical assessment of any remote sensing dataset that is to be used for further scientific applications.

c. Optimal estimation/Bayesian techniques

Although radiative closure and aircraft comparisons provide independent measures of uncertainty, these techniques themselves have associated uncertainties. Evaluations of atmospheric model simulations require rigorous uncertainty quantification for retrieved cloud properties. To address this, Bayesian or optimal estimation approaches have become popular as a way to uniquely quantify the uncertainty in measurements, retrieval assumptions, and forward models. Rodgers (2000) outlines the capacity for inverse methods to simultaneously retrieve cloud properties and their uncertainty by assuming that the measurements, the assumptions used to implement forward models, and all prior information can be represented probabilistically. The resulting solution then is also derived as a probability distribution with the mean of the solution representing the best estimate of the atmospheric state and the breadth of the distribution representing the uncertainty in the retrieval.

While the popular optimal estimation technique is essentially limited to assumptions of Gaussian statistics, other probabilistic techniques such as Markov chain Monte Carlo (Posselt and Mace 2014) are not thereby limited—the trade-off being in computational expense. These straightforward, but computationally expensive, approaches have been applied in several studies using ARM data. The more flexible Bayesian approach, which allows for a non-Gaussian distribution, has been applied

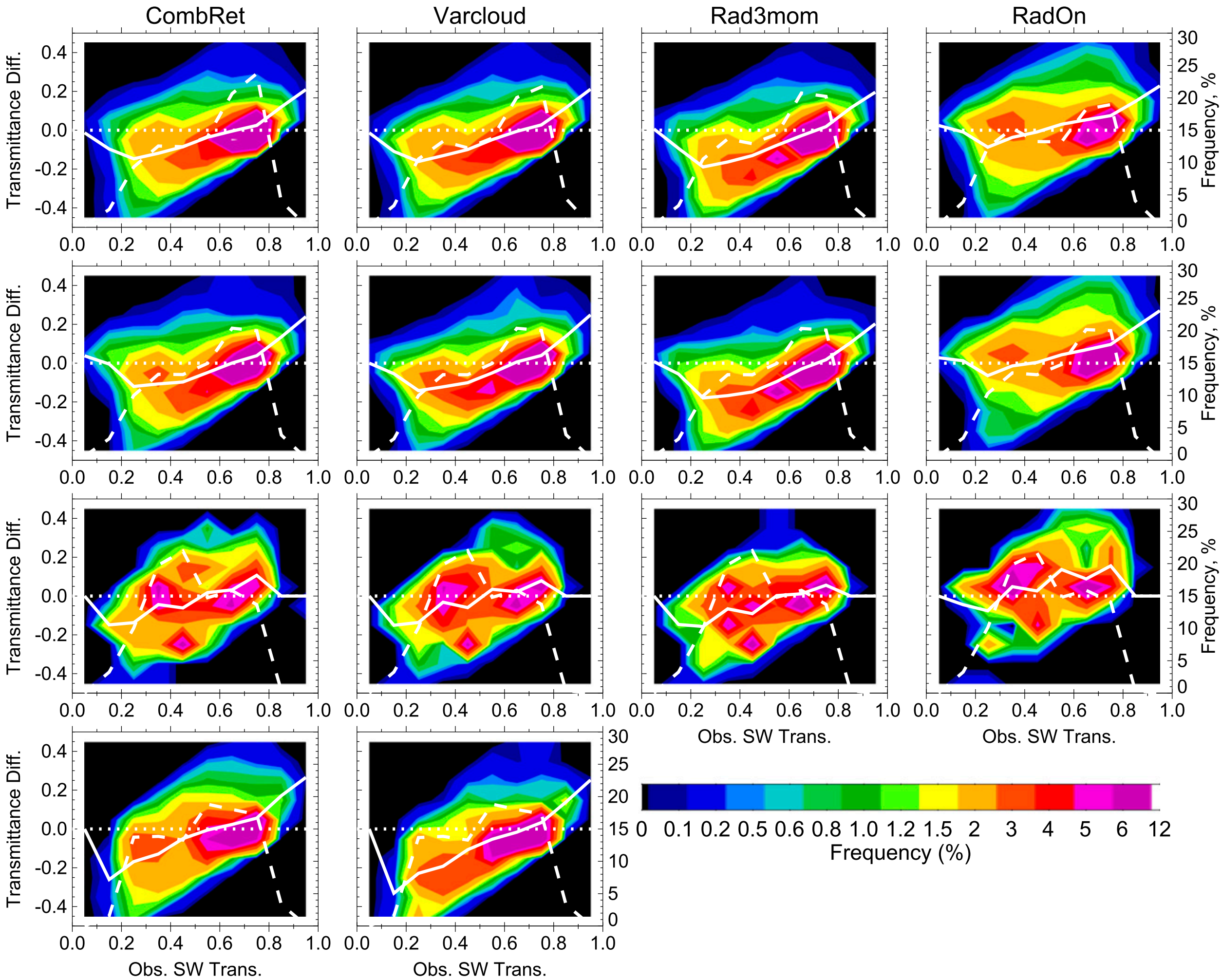

FIG. 19-9. Frequency of shortwave transmittance difference (observed − calculated) as a function of observed shortwave transmittance. Comparisons are for radiative transfer calculations using cloud microphysical results from two radar-lidar algorithms (CombRet and Varcloud) and two radar reflectivity-Doppler velocity algorithms (Rad3mom and RadOn). Each row (from top to bottom) represents: all retrievals; clouds only detected by radar; clouds detected by radar and lidar; and clouds only detected by lidar. The mean is given as a white line in each panel. [Figure from Comstock et al. (2013), courtesy of the *Journal of Geophysical Research*.]

to radar reflectivity and microwave radiometer measurements to retrieve LWC and r_e in low-level liquid clouds observed at the ARM Nauru site (McFarlane et al. 2002). The optimal estimation approach has been applied to cirrus (Mace et al. 2002; Delanoë and Hogan 2008; Deng and Mace 2008), low-level liquid clouds (Turner 2007; Cadeddu et al. 2013), and mixed-phase clouds (Turner 2005).

As our understanding of the prominent role of clouds in the climate system evolves, and numerical model capabilities push toward higher resolutions, information on cloud properties and processes is needed at increasingly finer detail. Cloud retrievals developed by ARM and other programs over the past couple of decades have offered a wealth of first-order information on basic cloud properties and their role in the climate system; this information has been used to evaluate and develop numerical models. The evolving demands for cloud products at higher spatial and temporal resolutions are placing stronger requirements on cloud retrievals and especially on quantifying retrieval uncertainties. As a result, more focus is needed in a number of key directions to both improve the overall cloud retrievals and better characterize their uncertainties. These directions include the following: identifying sources of uncertainty within both the measurements and retrieval framework, adding new measurement constraints and improving the accuracy of measurements, further developing forward models that more accurately represent the mapping of physical cloud-system properties to observational constraints, and building statistics concerning important physical processes upon which the retrievals are based (i.e., mass–dimension relationships and particle-size distributions in ice clouds). A path forward for improving retrieval algorithms and quantifying the associated uncertainty will be the focus of future efforts led, in part, by the recently formed Quantification of Uncertainty in Cloud Retrievals (QUICR) focus group.

5. ARM cloud retrievals into the future

Building on these significant contributions to cloud retrieval development over the past two decades, ARM is poised to make further advances. Recent innovation in observational technology and the acquisition of new instruments (Mather and Voyles 2013) will provide exciting measurements to stimulate a new surge of retrieval algorithm development in a number of directions.

These new ARM instruments present an array of additional constraints for basic retrievals of cloud microphysical properties. For example, each ARM site now contains multifrequency cloud and precipitation radars, such that each site has two to five different radar wavelengths that can be used simultaneously. Multiwavelength retrievals have been developed in the past (e.g., Gosset and Sauvageot 1992; Huang et al. 2009), but running these radar suites operationally year-round is sure to promote the development of new retrieval algorithms. Similarly, the addition of high spectral resolution (Eloranta 2005) and Raman lidars (Goldsmith et al. 1998; Turner et al. 2016, chapter 18) to many sites is a significant advancement that will bring much improved sensitivity at each site (e.g., Thorsen et al. 2013), and will be able to deliver true calibrated backscatter, which will facilitate the quantitative use of these measurements in advanced lidar-based and multisensor cloud retrievals. Other new instruments, such as the higher-frequency microwave radiometer observations (Cadeddu et al. 2013) and the shortwave spectrometer will play an important role in future cloud retrieval algorithms, providing critical new radiative constraints in bands that have not previously been exploited. However, the forward models used to simulate these observations must first be improved [e.g., improving the accuracy of the temperature dependence of liquid water absorption at microwave frequencies; Kneifel et al. (2014)].

Cloud dynamical properties also will be a focus of the near future. ARM has installed Doppler lidars at most sites that offer insight into low-level wind fields, vertical motions, and turbulence. These new measurements can be paired with radar-based information on vertical velocity and turbulence from within clouds to characterize the full cloud and subcloud dynamical environment. Importantly, this dynamical information can be combined with derived microphysical properties to study detailed cloud processes (e.g., Ghate et al. 2011; Luke and Kollias 2013). Additionally, enhanced radar Doppler spectra deconvolution techniques can be developed to distinguish the microphysical and turbulent contributions within identical sample volumes.

The introduction of scanning cloud radars to ARM sites will help the program to break free of the narrow zenith column above the sites and to better evaluate how representative column measurements are of regional processes. Scanning allows for innovative techniques to track clouds (e.g., Fielding et al. 2013) and to characterize spatial variability in new ways. Additionally, scanning measurements can be used to probe ice particle habit (e.g., Matrosov et al. 2012; Marchand et al. 2013), which can enhance our understanding of ice particle size distributions, particle growth regimes, fall speeds, and the assumptions used in bulk cloud retrievals. Scanning millimeter-wavelength cloud radars have never been operated in a continuous mode for extended periods of time, thus offering the unprecedented opportunity to examine multidimensional cloud structure in all seasons.

Precipitation is another exciting area of expansion and future development within ARM, as all sites have now been instrumented with scanning, polarimetric precipitation radars and enhanced surface-based disdrometers for quantifying precipitation properties. These additions offer the first operational polarimetric measurements at the ARM sites and the ability to evaluate and compare precipitation retrievals developed using cloud radars with those from traditional precipitation radars. Further, these enhancements present the possibility to simultaneously characterize both cloud and precipitation properties (e.g., Matrosov 2010), which will be useful for understanding precipitation formation processes, the mesoscale organization of storms, and other features.

One of the great challenges for cloud retrieval advancement will be in improving and developing the appropriate forward models through which the physical cloud–atmosphere system can be mapped onto these many new and existing measurements. For example, the temperature dependence of liquid water absorption at microwave frequencies must be improved over the full range of temperatures applicable for cloud processes of interest (Kneifel et al. 2014). Similar needs exist for representing new sophisticated lidar and radar measurements. For example, improved representations of lidar depolarization signals related to particle phase and habit are an important area of development. Robust polarimetric radar forward models, particularly for shorter wavelength radars that are sensitive to clouds, are also increasingly in demand. Additionally, simulators of radar Doppler spectra that can account for convolved cloud microphysical and dynamical conditions will help to unlock the vast information held in these spectra.

Together, these multiple avenues of advancement on cloud and precipitation retrievals will contribute toward improved operational, all-condition retrieval frameworks to obtain continuous, time–height cloud and precipitation products. Some of these methods will continue to combine disparate retrievals within a single framework that requires sophisticated logic for the correct application of techniques (i.e., the classification problem). However, new optimal estimation approaches also should be developed to combine larger suites of instruments within a single, broadly applicable retrieval algorithm to produce continuous estimates of both microphysical and dynamical properties. A further challenge moving forward will be to extend beyond bulk cloud properties and derive higher-order information on liquid droplet and ice particle size distributions.

Over the past two decades, ARM has established itself as a leader in developing and operating ground-based suites of instruments to characterize clouds. In that time, the program has grown and cloud-sensing instruments have become more robust and sophisticated. Paralleling this instrumental maturation, the program has supported similar progress in cloud retrieval development, leading to evermore advanced, complex, and comprehensive retrievals. The future trajectory of DOE-sponsored cloud retrieval development activities will build on ARM's extensive infrastructure and past accomplishments through coordination with the new DOE Atmospheric System Research Program and through enhanced collaboration with similar activities in Europe such as Cloudnet (Illingworth et al. 2007; Haeffelin et al. 2016, chapter 29). Together these programs will ensure that DOE continues to produce high-quality cloud properties datasets that are appropriate for studying cloud processes, evaluating models, constructing model parameterizations, and addressing key climate science questions.

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