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Airborne passive microwave geophysical retrievals and applications in assessing environmental and aerosol impacts on maritime convection

Corey G. Amiot

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AIRBORNE PASSIVE MICROWAVE GEOPHYSICAL RETRIEVALS AND APPLICATIONS IN ASSESSING ENVIRONMENTAL AND AEROSOL IMPACTS ON MARITIME CONVECTION

Corey G. Amiot

A DISSERTATION

Submitted in partial fulfillment of the requirements for the degree of Doctor of Philosophy in The Department of Atmospheric and Earth Science to The Graduate School of The University of Alabama in Huntsville May 2023

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Abstract

AIRBORNE PASSIVE MICROWAVE GEOPHYSICAL RETRIEVALS AND APPLICATIONS IN ASSESSING ENVIRONMENTAL AND AEROSOL IMPACTS ON MARITIME CONVECTION

Corey G. Amiot

A dissertation submitted in partial fulfillment of the requirements for the degree of Doctor of Philosophy

The Department of Atmospheric and Earth Science

The University of Alabama in Huntsville
May 2023

Improvements to NASA’s Advanced Microwave Precipitation Radiometer (AMPR) have yielded physically realistic brightness temperatures ($T_b$) from the Olympic Mountains Experiment / Radar Definition Experiment (OLYMPEX/RADEX) and Cloud, Aerosol and Monsoon Processes Philippines Experiment (CAMP$^2$Ex). Multi-linear regression equations, developed to retrieve integrated cloud liquid water (CLW), water vapor (WV), and 10-m wind speed (WS), were tested using simulations, deconvolved AMPR $T_b$ from OLYMPEX/RADEX, independent retrievals, and in situ data. Simulated retrievals yielded average CLW, WV, and WS root-mean-square deviations (RMSD) of 0.11 kg m$^{-2}$, 1.28 kg m$^{-2}$, and 1.11 m s$^{-1}$, respectively, when compared with modeled atmospheric profiles, with median absolute deviations (MedAD) of 2.26 x $10^{-2}$ kg m$^{-2}$, 0.22 kg m$^{-2}$, and 0.55 m s$^{-1}$. Applied to OLYMPEX/RADEX, the CLW, WV, and WS RMSD were 9.95 x $10^{-2}$ kg m$^{-2}$, 2.00 kg m$^{-2}$, and 2.35 m s$^{-1}$, respectively, against independent retrievals, and MedAD were 2.88 x $10^{-2}$ kg m$^{-2}$, 1.14 kg m$^{-2}$, and 1.82 m s$^{-1}$. Average WV (WS) MedAD against dropsondes were 1.95 kg m$^{-2}$ (1.34 m s$^{-1}$), further indicating strong retrieval performances. Expanding to CAMP$^2$Ex involved retrieval
improvements, validation, and science applications. CLW retrievals required modification for the maritime tropics, which yielded $1.94 \times 10^{-2}$ kg m$^{-2}$ RMSD against simulations. Validation against airborne Ku- and Ka-band radar-derived CLW produced high MedAD around 0.40 kg m$^{-2}$; however, polarimeter-derived CLW offered MedAD around $8.08 \times 10^{-2}$ kg m$^{-2}$. AMPR CLW decreases within polarimeter-derived cloud-top height > 4 km may signify accretion and/or mixed-phase onset. Mean WV (WS) absolute deviation against 144 dropsondes was within target uncertainty at 8.27% (1.76 m s$^{-1}$). Dropsonde-derived 0°C level height had moderate 0.49 (0.43) correlation with CLW (WS). Bulk correlations between nine dropsonde parameters and three convective metrics from AMPR and airborne radar across CAMP$^2$Ex were relatively weak. Comparisons between five remote-sensing convective metrics and airborne-lidar-derived aerosol concentrations were performed within stratified CAMP$^2$Ex environments in four sensitivity tests, wherein medium to relatively high aerosol concentrations were often directly correlated with convective intensity and frequency within favorable environments. Stratification using environmental lapse rates or K-Index generally yielded the highest correlations between convective metrics and aerosol concentrations.
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### List of Acronyms and Abbreviations

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<th>Full Name</th>
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<tbody>
<tr>
<td>1DVAR</td>
<td>One-Dimensional Variational</td>
</tr>
<tr>
<td>AGL</td>
<td>Above Ground Level</td>
</tr>
<tr>
<td>AMPR</td>
<td>Advanced Microwave Precipitation Radiometer</td>
</tr>
<tr>
<td>AMS</td>
<td>American Meteorological Society</td>
</tr>
<tr>
<td>AMSL</td>
<td>Above Mean Sea Level</td>
</tr>
<tr>
<td>AOS</td>
<td>Atmosphere Observing System</td>
</tr>
<tr>
<td>AOT</td>
<td>Aerosol Optical Thickness</td>
</tr>
<tr>
<td>APR-3</td>
<td>Airborne Precipitation and cloud Radar 3rd Generation</td>
</tr>
<tr>
<td>AVAPS</td>
<td>Advanced Vertical Atmospheric Profiling System</td>
</tr>
<tr>
<td>Bsc</td>
<td>Backscatter</td>
</tr>
<tr>
<td>CAMP²Ex</td>
<td>Cloud, Aerosol and Monsoon Processes Philippines Experiment</td>
</tr>
<tr>
<td>CAPE</td>
<td>Convective Available Potential Energy</td>
</tr>
<tr>
<td>CCN</td>
<td>Cloud Condensation Nuclei</td>
</tr>
<tr>
<td>CLW</td>
<td>Integrated Cloud Liquid Water Path</td>
</tr>
<tr>
<td>COT</td>
<td>Cloud Optical Thickness</td>
</tr>
<tr>
<td>CTH</td>
<td>Cloud-Top Height</td>
</tr>
<tr>
<td>EIA</td>
<td>Earth Incidence Angle</td>
</tr>
<tr>
<td>Ext</td>
<td>Extinction</td>
</tr>
<tr>
<td>GDAS</td>
<td>Global Data Assimilation System</td>
</tr>
<tr>
<td>GEOS-5</td>
<td>Goddard Earth Observing System Model, Version 5</td>
</tr>
<tr>
<td>GMI</td>
<td>GPM Microwave Imager</td>
</tr>
</tbody>
</table>
GPM: Global Precipitation Measurement

IMPACTS: Investigation of Microphysics and Precipitation for Atlantic Coast-Threatening Snowstorms

IPHEx: Integrated Precipitation and Hydrology Experiment

LCL: Lifting Condensation Level

LFC: Level of Free Convection

LR: Lapse Rate

LWC: Liquid Water Content

MedAD: Median Absolute Deviation

MSFC: Marshall Space Flight Center

NASA: National Aeronautics and Space Administration

NCEP: National Centers for Environmental Prediction

NEDT: Noise-Equivalent Differential Temperature

NPOL: NASA S-band Dual-Polarimetric Radar

OLYMPEX: Olympic Mountains Experiment

ORACLES: Observations of Aerosols above Clouds and their Interactions

PCA: Principal Component Analysis

QC: Quality Control

RADEX: Radar Definition Experiment

RHI: Range-Height Indicator

RMSD: Root-Mean-Square Deviation

RSP: Research Scanning Polarimeter

RTM: Radiative Transfer Model

SF: Science Flight

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SST  Sea Surface Temperature
T_b  Brightness Temperature
T_d  Dew Point Temperature
TMI  TRMM Microwave Imager
TPW  Total Precipitable Water
TRMM  Tropical Rainfall Measuring Mission
UAH  The University of Alabama in Huntsville
V_r  Doppler Velocity
WV  Total Precipitable Water Vapor
WS  10-Meter Wind Speed
Z_H  Equivalent Radar Reflectivity Factor
Chapter 1. Introduction, Purpose, and Overview

1.1 Introduction and Purpose

Airborne instruments provide a unique perspective on many aspects of our atmosphere. Their combination of relatively high spatial and temporal resolutions, flexibility in selecting targets for sampling, and the ability to simultaneously acquire both in situ and remotely sensed data make them useful to a variety of applications and science questions. Despite some associated shortfalls (e.g., limited regional coverage, both horizontally and vertically), recent field campaigns have been designed to employ these airborne instruments in studies that focus on clouds, convection, precipitation, and aerosols. These atmospheric features are of interest to ongoing research given their importance in the global energy and water cycles, local and regional impacts, changing climates, and efforts to better understand how these features behave under various conditions, both individually and synergistically. Due to the implications and applications of the results from such airborne studies, it is imperative for the collected data to be of high quality.

The overarching purposes of this doctoral dissertation are: 1) to provide a detailed description of the airborne geophysical retrieval methods that have been developed, tested, and validated following relatively recent improvements to the National Aeronautics and Space Administration (NASA) Advanced Microwave Precipitation
Radiometer (AMPR); 2) to demonstrate the utility of these retrievals in addressing important science questions related to maritime convection, environmental conditions, and aerosol concentrations; and 3) to investigate potential influences of environmental conditions and aerosol concentrations on maritime tropical convection by employing these AMPR retrievals alongside other airborne datasets. AMPR was the primary instrument used in this study given its extensive involvement in recent NASA airborne field campaigns, such as: the Integrated Precipitation and Hydrology Experiment (IPHEx; Barros et al. 2016), Olympic Mountains Experiment (OLYMPEX) and Radar Definition Experiment (RADEX; Houze et al. 2017), Observations of Aerosols above Clouds and their Interactions (ORACLES; Redemann et al. 2021), Investigation of Microphysics and Precipitation for Atlantic Coast-Threatening Snowstorms (IMPACTS; McMurdie et al. 2022), and Cloud, Aerosol and Monsoon Processes Philippines Experiment (CAMP²Ex; Reid et al. 2023). These field campaigns cover a wide range of regional and climatological regimes, with a corresponding range of science questions posed for each study, which make AMPR data and geophysical retrievals valuable assets. Prior to the work covered herein, a fairly limited number of studies had employed AMPR data following its dual-polarization upgrade in the early 2010s, and this upgrade to the AMPR system had not been published in the peer-reviewed literature. In regards to the latter, it must be acknowledged that the research presented herein builds upon years of effort contributed by many AMPR scientists and engineers.

This dissertation is organized into five primary chapters, with chapters 2, 3, and 4 each serving as a standalone manuscript. Chapter 2 has been published in the American Meteorological Society (AMS) Journal of Atmospheric and Oceanic Technology
(JTECH), referenced as Amiot et al. (2021), though minor text edits have been made throughout chapter 2. It should be clarified that components of Amiot et al. (2021)’s abstract and section 1.1 have been extracted and intertwined in this dissertation’s abstract and chapter 1, respectively, while their section 1.2 onward are presented in chapter 2. Chapter 3 has been prepared, but not yet submitted, for peer-reviewed publication in JTECH, and has incorporated suggestions from its co-authors. Chapter 4 was recently developed with the intention to eventually submit to the AMS Journal of Applied Meteorology and Climatology (JAMC).

1.2 NASA’s Advanced Microwave Precipitation Radiometer (AMPR)

AMPR is a cross-track scanning total power radiometer that operates at four radio-frequency channels with central frequencies at: 10.7, 19.35, 37.1, and 85.5 GHz (Spencer et al. 1994). These frequencies are sensitive to radiation emitted from, or scattered by, raindrops, precipitation ice, liquid and ice cloud hydrometeors, and/or water vapor (Spencer et al. 1994). AMPR data are stored in 50 cross-track pixels per scan, measured ±45° from nadir, with the footprint resolution of each pixel varying with aircraft altitude. AMPR’s scanning mode typically involves running cross-track scans four or eight times consecutively before its mirror rotates to view onboard hot and cold calibration targets, and the cycle repeats. The AMPR system, as will be explained in detail in chapter 2, currently operates with two orthogonal receivers at each of its four frequencies, which enable raw mixed-polarization data to be deconvolved into their horizontal and vertical components; these deconvolutions were not possible unambiguously prior to the system’s dual-polarization upgrade (Amiot et al. 2021).
During the OLYMPEX/RADEX campaign, AMPR flew onboard a NASA ER-2 high-altitude research aircraft. At the 20-km primary flight altitude for the ER-2 during OLYMPEX/RADEX, the 10.7- and 19.35-GHz frequencies have a footprint diameter of roughly 2.8 km, while the 37.1- and 85.5-GHz frequencies have footprint diameters of approximately 1.5 and 0.6 km, respectively. However, all AMPR data are sampled at the 85.5-GHz (0.6 km) channels’ intervals in the along-scan (i.e., cross-track) direction (Spencer et al. 1994). In contrast, during CAMP$^2$Ex, AMPR flew onboard NASA’s P-3 aircraft, which frequently changed altitude throughout a given flight, resulting in AMPR’s footprint resolution varying from approximately 94–220 m throughout the campaign.

1.3 Science Questions and Hypotheses

As previously mentioned, the first part of this dissertation involves a detailed description of AMPR’s geophysical retrievals, including their derivation, testing, and validation. These tests include both simulated and observational datasets, with the latter involving data from OLYMPEX/RADEX and CAMP$^2$Ex. While some science applications are discussed in chapter 2 for OLYMPEX/RADEX, the bulk of the science analyses in this dissertation focus on CAMP$^2$Ex in chapters 3 and 4. Due to AMPR’s ability to provide useful geophysical information about convective elements and their surrounding environments, especially when viewed against a water background, the decision was made to focus on maritime convection in these studies. Further analyses were devoted to the influences of environmental conditions and aerosol concentrations on convection due to the importance of these features in CAMP$^2$Ex science objectives and
the variety of instruments involved in CAMP$^2$Ex to study these phenomena. The five specific science questions addressed in this dissertation are as follows:

1) What trends are present in AMPR’s tropical geophysical retrievals, and how do they compare with expectations based on prior studies?

2) What information can AMPR’s cloud liquid water (CLW) retrievals provide about cloud and precipitation processes?

3) What relations can be found between AMPR’s retrievals and dropsonde data on a flight-by-flight basis, and what are their physical explanations?

4) How do radiometer- and radar-based metrics of storm intensity and frequency vary with different dropsonde-measured environmental indicators of convective intensity and/or potential throughout CAMP$^2$Ex?

5) When binned into similar environmental groups, how do the same radar- and radiometer-based metrics of storm intensity and frequency vary with lidar-based observations of aerosol concentration?

Based on prior studies, the following hypotheses were posed at the outset of this study:

1) AMPR’s geophysical retrievals will yield values that are similar to those observed in past studies, and their uncertainties will fall within the ranges established by prior works;

2) AMPR’s CLW retrievals will be proportional to the squared value of cloud-top height, and they will increase in the presence of deeper convection;

3) The geophysical retrievals are directly related to environmental conditions that are indicative of convective potential;
4) Each remote-sensing parameter associated with convective intensity and/or frequency will be directly correlated with dropsonde-measured parameters that have direct physical connections to convective intensity and/or frequency;

5) Higher aerosol concentrations are directly related to more intense convection and a greater frequency of convection observed throughout a given flight.
Chapter 2. Retrieval Derivations and Testing: OLYMPEX/RADEX

This chapter provides an overview of AMPR’s polarimetric upgrade, derivation of multi-linear geophysical retrieval equations using data from the upgraded AMPR system, performances of the retrieval equations against simulated atmospheric profiles, and the results of testing these retrieval methods using data from OLYMPEX/RADEX. OLYMPEX took place from Fall 2015 – Spring 2016 in collaboration with RADEX (Houze et al. 2017). The primary goal of OLYMPEX was to examine how precipitation is affected by flow over the Olympic Mountains of Washington in the United States, while RADEX focused on improving satellite-based retrievals of cloud and precipitation properties. Numerous instruments, including AMPR, were deployed to the study domain around northwestern Washington. This study domain will be the focus area for testing discussed in this chapter, with expansion to other geographical areas and climatological regimes explored in chapters 3 and 4. This chapter has been published in AMS JTECH as Amiot et al. (2021), and all text, figures, and tables are adapted from that publication (© copyright 2021 American Meteorological Society). In addition to Biswas et al. (2017), Biswas (2016, unpublished technical report) was heavily referenced when forming the discussion of AMPR’s upgrade and calibration, primarily in section 2.1.
2.1 AMPR Polarimetric Upgrade and Calibration

AMPR’s antenna system consists of a dedicated feedhorn for the 10.7-GHz channel and a separate feedhorn for the higher-frequency channels. Both feedhorns have dual-orthogonal polarization outputs for each frequency channel. In past studies (e.g., Vivekanandan et al. 1993; Smith et al. 1994; Evans et al. 1995; McGaughey et al. 1996; Cecil et al. 2010), only one feedhorn polarization was measured using a single receiver for each channel. AMPR’s two fixed feedhorns combined with cross-track scanning via a rotating mirror resulted in brightness temperature ($T_b$) scenes that were vertically polarized at one edge of the scan, horizontally polarized at the other edge, and mixed polarization for intermediate scan angles. With this configuration, it was not possible to unambiguously retrieve true horizontally and vertically polarized $T_b$ across the entire AMPR scene. To account for this, a second receiver was added for each channel to measure the orthogonal feedhorn polarization. This allowed for orthogonal mixed-polarization $T_b$ values to be gathered across the entire AMPR scene, from which vertical- and horizontal-polarization $T_b$ suitable for geophysical parameter retrievals can be estimated. Due to the fixed feedhorns and rotating mirror, AMPR scene polarization basis rotates with respect to the feedhorn polarization basis for each scan angle. A diagram presenting these system and scan properties can be found in Fig. 2.1.

Following Piepmeier et al. (2008), as discussed in Biswas (2016, unpublished technical report), for a rotation angle $\phi'$, the relationship between $T_b$ in the scene polarization basis and measured $T_b$ in the feedhorn polarization basis is given by
FIG. 2.1. Diagram illustrating the polarization mixing geometry present within the AMPR system during a typical flight. Within this diagram, $\phi$ is the scan angle, $\theta$ is the reflector-normal angle, $\psi$ is the polarization-rotation angle of the feedhorn, and $\alpha = \phi'$ is the polarization-basis-rotation angle; all other variables correspond to their respective vectors or angles as indicated within the diagram. Adapted from Biswas et al. (2017).

$$\vec{T}_f = \begin{pmatrix} T_{fA} \\ T_{fB} \\ T_{f3} \\ T_{f4} \end{pmatrix} = \begin{pmatrix} \sin^2(\phi') & \cos^2(\phi') & -\frac{1}{2}\sin(2\phi') & 0 \\ \cos^2(\phi') & \sin^2(\phi') & \frac{1}{2}\sin(2\phi') & 0 \\ \sin(2\phi') & -\sin(2\phi') & -\cos(2\phi') & 0 \\ 0 & 0 & 0 & 1 \end{pmatrix} \begin{pmatrix} T_v \\ T_h \\ T_3 \\ T_4 \end{pmatrix} = V(\phi') \cdot \vec{T}, \quad (1)$$

where $\vec{T}_f$ is measured $T_b$ vector at the feedhorn, $\vec{T}$ is true scene $T_b$ vector, $T_b$ subscripts $v$, $h$, 3, and 4 indicate vertically polarized, horizontally polarized, 3rd Stokes, and 4th Stokes $T_b$, respectively, and nominally for AMPR $\phi' = \phi - 45^\circ$, where $\phi$ is off-nadir scan angle. In Eq. 1, $\phi$ is measured positive (negative) toward the starboard (port) side of the observation platform. The 45-degree difference between $\phi'$ and $\phi$ is due to the AMPR
feedhorn polarization axes being rotated 45° about the scan axis. From Eq. 1, exact estimation of $T_v$ and $T_h$ requires measurement of $T_3$, which is not presently measured in the AMPR system. For AMPR $T_b$ scenes where the vertically and horizontally polarized signals are uncorrelated, Eq. 1 can be simplified to produce

$$\bar{T}_f = \begin{pmatrix} T_{fA} \\ T_{fB} \end{pmatrix} = \begin{bmatrix} \sin^2(\phi') & \cos^2(\phi') \\ \cos^2(\phi') & \sin^2(\phi') \end{bmatrix} \begin{pmatrix} T_v \\ T_h \end{pmatrix} = \bar{u}(\phi') \cdot \bar{T},$$

(2)

the reverse transformation of which is given by

$$\bar{T} = \bar{u}(-\phi') \cdot \bar{T}_f,$$

(3)

which can be used to estimate true horizontally and vertically polarized $T_b$ from the mixed-polarization $T_b$ measured at the orthogonal channels for each AMPR receiver. For a wind-roughened ocean scene observed by AMPR, $T_v$ and $T_h$ are not completely uncorrelated and there exists a very weak wind-direction-dependent $T_3$ signal for low-to-moderate wind speeds. The error resulting from this is ignored in this study. Eqs. 2 and 3 are specific to the AMPR system, as measurements of $T_3$ and $T_4$ are not recorded; thus, $\bar{V}(\phi') \cdot \bar{T}$ in Eq. 1 is different than $\bar{u}(\phi') \cdot \bar{T}$ in Eq. 2. It should be noted that Eq. 2 reaches singularity at $\phi' = 0°$, which coincides with an AMPR scan angle of $\phi = 45°$ (i.e., the edge of the swath). At this angle, Eq. 3’s solution diverges. As a result, uncertainty in input $T_b$ increases for scan angles nearer the edge of the scan, which must be taken into consideration when interpreting results around the swath edges.

Raw AMPR measurements of radiometer counts for each frequency and polarization channel are converted to physically meaningful $T_b$ using a two-point linear calibration in which one radiometrically “hot” and one “cold” target with known $T_b$ values are sequentially viewed to determine radiometer system gain and $T_b$ offset. In the typical scan sequence during OLYMPEX/RADEX, AMPR’s mirror rotated to view each
calibration target (hereafter simply “target”) after every fourth scan. The “hot” target is controlled by a heater and is typically 318 K. However, the “cold” target is cooled using ambient air from around the aircraft, and thus its temperature varies with aircraft altitude. It should be noted that the quantity derived after applying gain and offset corrections to the radiometer counts is proportional to the total power entering the antenna aperture from all possible directions, which is known as antenna temperature. For geophysical retrievals, the total power received by the antenna main beam is of interest, which is $T_b$.

There are three dominant error sources in deriving $T_b$ from antenna counts: error in estimation of receiver gain and offset, antenna pattern correction, and complicated polarization mixing geometry. For receiver gain and offset correction, the accuracy of two-point calibration depends on knowledge of hot and cold target $T_b$ observed by AMPR. The targets are designed to be highly emissive (i.e., > 99%), and their physical temperatures are measured using a platinum resistance thermometer, which yields accurate estimation of target $T_b$. However, in some cases, particularly for the 10.7-GHz channel, the antenna beam over illuminates the targets, yielding uncertainty in target $T_b$. To compensate, a correction is applied to the target temperatures, but some residual effects remain. For antenna pattern correction, accurate knowledge of AMPR’s antenna pattern is needed for each scan position to model energy entering the antenna from solid angles outside of the main beam. Complicated polarization mixing geometry due to AMPR’s fixed feedhorns and rotating reflector (Fig. 2.1) involves three key angles:

- Polarization-Rotation Angle ($\psi$), the angle between the feedhorn polarization axis and the instrument zenith direction, which is designed to be 45° for AMPR;
• Reflector-Normal Angle ($\theta$), the angle between the reflector normal and the reflector rotation axis. This angle typically points along the flight direction and is designed to be $45^\circ$ so the antenna beam points toward nadir in the middle of an AMPR scan;

• Scan Angle ($\phi$), the rotation angle of the mirror, with $\phi = 0^\circ$ at nadir.

Any deviation in these angles from nominal values may result in error during dual-polarization deconvolution when nominal values are assumed. In addition to these three error sources, cross-polarization leakage at the feedhorn may exist due to non-ideal nature of the transducer that separates the orthogonal polarizations. A generalized model for AMPR $T_b$ at any $\phi$ is given by

$$T_{b(\phi)} = (1 - \eta) [T_{b,v} \cdot A(\theta,\psi,\phi) + T_{b,h} \cdot B(\theta,\psi,\phi)] + \eta [T_{b,v} \cdot B(\theta,\psi,\phi) + T_{b,h} \cdot A(\theta,\psi,\phi)],$$  \hspace{1cm} (4)

where $\eta$ is cross-polarization fraction, and $A$ and $B$ are mixing weights of the polarization (Weng et al. 2003). With nominal values of $\theta$ and $\psi$, values of $A$ and $B$ are trigonometric functions of $\phi$ only, which simplifies dual-polarization deconvolution.

2.2 Geophysical Retrievals Using Microwave Radiometer

Many studies have focused on obtaining geophysical information from radiometric data. Several of these efforts aimed to calculate surface rain rates (e.g., Kummerow et al. 1996; Wentz and Spencer 1998; Shin and Kummerow 2003; Bowman et al. 2009) and hydrometeor properties (e.g., Smith et al. 1994; Evans et al. 1995; Leppert and Cecil 2015) from airborne and spaceborne platforms. Additional studies utilized microwave radiometers to estimate other geophysical parameters. For example, Hong and Shin (2013) investigated methods to retrieve sea-surface wind speed from
spaceborne microwave radiometers. Amarin et al. (2012) and Cecil and Biswas (2017) developed methods to retrieve wind speeds around tropical systems using aircraft-based C-band microwave radiometer, while Wentz and Spencer (1998) developed an algorithm to simultaneously retrieve cloud liquid water, water vapor, wind speed, and rain rate using the Special Sensor Microwave / Imager, following Wentz (1997). Similar work was performed by Biswas et al. (2017), who followed the methods of Wentz and Meissner (2000) and Wentz and Meissner (2007) to develop geophysical retrieval equations before applying them to AMPR data from OLYMPEX/RADEX.

The physical bases for these retrievals are rooted in properties of a calm ocean surface and atmospheric constituents when viewed at microwave frequencies. As described in Wilheit and Chang (1980), a calm ocean surface has very low emissivity due to water’s large dielectric constant. Wind roughens the ocean surface and generates foam, increasing ocean surface emissivity, especially when viewed at off-nadir scan angles (Wilheit and Chang 1980). In contrast to the radiometrically cool ocean, liquid hydrometeors in the atmosphere yield higher $T_b$ due to their higher emissivity, which is highly dependent on wavelength as Mie (1908) resonance and atmospheric absorption become more prominent at higher frequencies (Wilheit and Chang 1980). In addition, when viewed from airborne or spaceborne radiometers, atmospheric effects must be considered when computing $T_b$, as various atmospheric constituents (e.g., oxygen, water vapor, etc.) absorb and scatter shortwave and longwave radiation.

Utilizing these radiative properties, it is possible to retrieve column-integrated cloud liquid water, water vapor, and 10-m wind speed over the ocean using $T_b$ at multiple frequencies within the microwave spectrum. For AMPR’s channels, 10.7 GHz is most
capable of viewing the ocean surface due to its relatively low attenuation, while 19.35 GHz is partially influenced by cloud water, 37.1 GHz is strongly affected by cloud water, and 85.5 GHz is most sensitive to cloud particles (Spencer et al. 1994). In addition, high water vapor emissions may yield relatively high $T_b$ at 85.5 GHz (Spencer et al. 1994). Section 2.3 below will describe how these properties were used to develop, train, and check geophysical retrieval equations for AMPR data via numerical simulations, with an uncertainty analysis from these simulations presented in section 2.4. Application of the retrieval equations to OLYMPEX/RADEX data is discussed in section 2.5, the results of which are shown in section 2.6. Section 2.7 presents a summary and future work.

2.3 Forming the Retrieval Equations

The methods discussed herein and in section 2.5 follow Biswas et al. (2017). To develop multi-linear regression equations for the geophysical retrievals, 523,176 globally distributed atmospheric profiles from the Global Data Assimilation System (GDAS; NCEP 2000) were used to form a $T_b$ dataset. Cloud-top and cloud-bottom properties were obtained from ocean climatology (Wisler and Hollinger 1977). When deriving this physical $T_b$ dataset, instead of using the sea-surface temperature (SST) and wind speed data from the GDAS profiles, SST was randomly varied from 0 to 30°C and wind speed was randomly varied from 0 to 20 m s$^{-1}$, ignoring wind direction. This was done to decouple the atmosphere and sea surface when forming the $T_b$ dataset that would be used to train the retrieval equations.

The resulting physical $T_b$ dataset was used in a radiative transfer model (RTM) to simulate $T_b$ that would be observed by AMPR. Within the RTM, following Biswas et al. 
(2013), atmospheric absorption coefficients were calculated using Rosenkranz models for cloud liquid water (Liebe et al. 1991), oxygen (Liebe et al. 1991), nitrogen (Rosenkranz 1993), and water vapor (Rosenkranz 1998). While residual uncertainties in these models must be considered, it is worth noting that these absorption models were used in several independent studies during the Global Precipitation Measurement (GPM) Cross-Calibration activity (Biswas et al. 2013), and have been found to provide an acceptable standard over the AMPR frequency range. The emissivity model in Meissner and Wentz (2012) was used to compute surface emission and scattering; this model was developed and tested with many well-calibrated microwave radiometers (Meissner and Wentz 2012), and is acceptable for use with AMPR’s frequencies.

These models yielded the following general expression, which is adapted from Meissner and Wentz (2012), for top-of-atmosphere $T_b$:

$$T_{B,p} = T_{BU} + \tau \cdot E_p \cdot T_s + \tau \cdot T_{B\Omega},$$

where $T_{B,p}$ is top-of-atmosphere $T_b$, $T_{BU}$ is upwelling atmospheric $T_b$, $\tau$ is atmospheric transmissivity, $E_p = 1 - R_p$ where $R_p$ is sea-surface reflectivity, $T_s$ is SST, and $T_{B\Omega}$ is downwelling sky radiation scattered by the ocean surface. AMPR-observed $T_b$ values were simulated for Earth-incidence angle (EIA) values of 0 to 50° at a 0.2° increment, and 0.5 K of Gaussian noise was introduced into the RTM to maintain stability (Wentz and Meissner 2000). This 0.5 K of Gaussian noise is within AMPR’s noise-equivalent differential temperature (NEDT), which was determined to be 0.5–1.0 K during OLYMPEX/RADEX (not shown), and thus represents the uncertainty in AMPR-observed $T_b$ values. Since this noise was introduced into the simulated $T_b$ values before their use in training the regression equations, the noise is uncorrelated between the two
polarizations. Other sources of uncertainty exist in the simulations, such as uncertainty in GDAS SST, but these effects have been neglected due to their relatively small magnitude. For example, Bhargava et al. (2018) noted that GDAS SST was robust enough to be used as “truth” values in their study, and yielded an average bias ≤ 0.5 K (albeit, during the month of June). Uncertainties in EIA have also been neglected, as these are typically around 0.1°, which results in T_b uncertainty of 0.1–0.2 K (albeit, for conically scanning microwave radiometers; Berg et al. 2013).

Multi-linear regression was performed on the simulated T_b data (from Eq. 5) to derive coefficients for the geophysical retrieval equations, following Wentz and Meissner (2000). The geophysical parameters for which equations were developed in this study were: column-integrated cloud liquid water (CLW), column-integrated total precipitable water (herein “water vapor”; WV), and 10-m wind speed over the ocean (WS). The general forms of the retrieval equations are:

\[
\text{CLW (mm)} = a_0 + a_1 \cdot \ln(290 - T_{b19v}) + a_2 \cdot \ln(290 - T_{b19h}) + a_3 \cdot \ln(295 - T_{b85v}) + a_4 \cdot \ln(295 - T_{b85h}),
\]

\[
\text{WV (mm)} = a_0 + a_1 \cdot T_{b10v} + a_2 \cdot T_{b10h} + a_3 \cdot \ln(290 - T_{b19v}) + a_4 \cdot \ln(290 - T_{b19h}) + a_5 \cdot \ln(290 - T_{b37v}) + a_6 \cdot \ln(290 - T_{b37h}) + a_7 \cdot \text{SST},
\]

\[
\text{WS (m s}^{-1}) = a_0 + a_1 \cdot \ln(285 - T_{b10v}) + a_2 \cdot \ln(285 - T_{b10h}) + a_3 \cdot T_{b10v}^2 + a_4 \cdot T_{b10h}^2 + a_5 \cdot (T_{b10v} \cdot T_{b10h}) + a_6 \cdot T_{b19v} + a_7 \cdot T_{b19h} + a_8 \cdot T_{b85v}^2 + a_9 \cdot T_{b85h}^2 + a_{10} \cdot (T_{b19v} \cdot T_{b19h}) + a_{11} \cdot T_{b37v} + a_{12} \cdot T_{b37h} + a_{13} \cdot T_{b37v}^2 + a_{14} \cdot T_{b37h}^2 + a_{15} \cdot (T_{b37v} \cdot T_{b37h}) + a_{16} \cdot \text{SST},
\]

where the “a” terms are regression coefficients, T_b is in Kelvin, v and h subscripts indicate vertical and horizontal polarization, respectively, the 10, 19, 37, and 85 subscripts indicate the 10.7-, 19.35-, 37.1-, and 85.5-GHz AMPR channels, respectively,
and SST is sea-surface temperature in K. Coefficients in Eqs. 6–8 were generated for each AMPR EIA as seen in Fig. 2.2. The AMPR channels used in Eqs. 6–8 and the modifications to each $T_b$ (e.g., use of natural logarithms) were determined via an empirical analysis (not shown) during which more than 100 regression equations were tested and the combinations of channels that yielded the most optimal tradeoffs between low retrieval error (i.e., how error in the retrieved variable is affected by variations in that variable) and crosstalk errors (i.e., how error in the retrieved variable is affected by variations in other variables) were selected. As an initial test of Eqs. 6–8, mean retrieval and crosstalk errors (i.e., deviations herein) across the 523,176 GDAS simulations were calculated using the differences between the geophysical values output from Eqs. 6–8 and the same geophysical parameters observed in the GDAS profiles, averaged across all EIAs. In addition to mean retrieval and crosstalk error, the retrieval root-mean-square deviation (RMSD) was calculated to obtain a more robust measurement of retrieval uncertainty. For eventual comparison with dropsonde data from OLYMPEX/RADEX, which, as will be discussed in sections 2.5 and 2.6, had far fewer data points available than the simulations, median absolute deviation (MedAD) was also calculated for all AMPR pixels (i.e., 0 to n) as

$$\text{MedAD} = \text{median} \left( |\text{predicted}_{0,n} - \text{observed}_{0,n}| \right).$$

(9)

It should be noted that Eq. 8 is designed to calculate any 10-m wind speed value over the ocean, which differs from past methods (e.g., Wilheit and Chang 1980; Hong and Shin 2013) that utilized different equations for different ranges of wind speeds. This reduces artifacts that may occur when comparing multi-step calculations to those obtained via other methods, but may increase retrieval error for lower wind speeds (e.g., Hong and
FIG. 2.2. Plots of the regression coefficients in the retrieval equations for cloud liquid water (top-left; red lines), water vapor (center-left; green lines), and 10-m wind speed over the ocean (bottom-left; blue lines) as a function of AMPR Earth-incidence angle (EIA). Eqs. 6–8 are shown in the right column next to their respective variable.

\[
\text{CLW (mm)} = a_0 + a_1 \cdot \ln(290 - T_{b19v}) + a_3 \cdot \ln(290 - T_{b19h}) + a_4 \cdot \ln(290 - T_{b85v}) + a_5 \cdot \ln(290 - T_{b85h})
\]

\[
\text{WV (mm)} = a_0 + a_1 \cdot T_{b10v} + a_2 \cdot T_{b10h} + a_4 \cdot \ln(290 - T_{b19v}) + a_5 \cdot \ln(290 - T_{b19h}) + a_6 \cdot \ln(290 - T_{b37v}) + a_7 \cdot \ln(290 - T_{b37h}) + a_7 \cdot \text{SST}
\]

\[
\text{WS (m s}^{-1}\text{)} = a_0 + a_1 \cdot \ln(285 - T_{b10v}) + a_2 \cdot \ln(285 - T_{b10h}) + a_3 \cdot T_{b10v}^2 + a_4 \cdot T_{b10h}^2 + a_5 \cdot (T_{b10v} - T_{b10h}) + a_6 \cdot T_{b19v} + a_7 \cdot T_{b19h} + a_8 \cdot T_{b37v} + a_9 \cdot T_{b37h} + a_{10} \cdot T_{b37v}^2 + a_{11} \cdot T_{b37h}^2 + a_{12} \cdot (T_{b37v} - T_{b37h}) + a_{13} \cdot T_{b37v} \cdot T_{b37h} + a_{14} \cdot T_{b37v}^2 + a_{15} \cdot T_{b37h}^2 + a_{16} \cdot \text{SST}
\]
Furthermore, Eq. 7 does not utilize AMPR’s 85.5-GHz channel, despite the potential influence from high WV at this frequency (e.g., Spencer et al. 1994). This decision was made based on a brief sensitivity test, which showed little improvement in WV retrieval RMSD compared to Eq. 7 (i.e., difference of approximately 3.0 x 10^{−2} mm) when 85.5-GHz data were included in the regression equation, but this may be explored further in future work.

Lastly, it has been demonstrated how WV is strongly correlated with SST (e.g., Stephens 1990). The decision to include SST in Eq. 7 as a regression variable resulted from testing various methods to remove WV cross-track stripes observed in Biswas et al. (2017), which were largely successful. However, variance in the WV retrievals during a given flight are not related to SST, since, as discussed in section 2.5, the median SST observed during the flight was used as the SST value for all AMPR pixels during that flight. To confirm this, a Principal Component Analysis (PCA; not shown) was performed, which, after standardizing the data, demonstrated that approximately 97.8% of the variance in simulated T_b was explained by the first two principal components. The correlation between SST and these two principal components was extremely small (i.e., magnitude of 10^{−10} or less), further indicating essentially no variance explanation from the SST term. Thus, variations in WV calculated via Eq. 7 were solely due to variations in AMPR T_b during the flight.

In this same regard, Wilheit and Chang (1980) noted that including T_b from a frequency around 37.1 GHz only slightly improved WS retrieval. During the sensitivity tests, minimal improvement in WS retrieval was noted after including 37.1-GHz T_b. However, it was also noted that 37.1-GHz T_b significantly reduced cross-track stripe
artifacts that resulted from use of a single WS equation across all ranges of wind speed, which warranted its inclusion in Eq. 8.

2.4 Statistical Results of Retrieval Simulations

This section presents the results of geophysical parameters calculated using Eqs. 6–8, with simulated $T_b$ values from Eq. 5 as inputs, compared to geophysical values obtained from the 523,176 GDAS profiles. Retrieval RMSD for each parameter as a function of EIA is shown in Fig. 2.3. Starting with CLW, the trend of CLW versus EIA in Fig. 2.3 demonstrates that retrieval error depends strongly on EIA. For EIA around 0°, CLW RMSD is at its maximum, 0.116 mm, primarily due to the similarity between horizontally and vertically polarized $T_b$ at nadir (e.g., Wilheit and Chang 1980), which makes it difficult to interpret differences between $T_b$ from AMPR’s orthogonal receivers for near-nadir EIAs. CLW RMSD decreases farther from nadir as horizontally and vertically polarized $T_b$ values diverge (all else being equal), reaching a minimum of $9.8 \times 10^{-2}$ mm around 43°. The slight RMSD increase after EIA = 43° is likely due to the greater distance in the atmosphere through which the AMPR signal must travel.

CLW retrieval and crosstalk errors averaged across all EIAs for a range of geophysical values can be found in Fig. 2.4. From Fig. 2.4, mean CLW retrieval error was around 0 mm for the 0.025–0.3 mm CLW range and standard deviation remained within 0.1 mm, indicating that Eq. 6 produced fairly consistent results across a range of CLW. Crosstalk errors of CLW with WV, WS, and SST were also fairly low, albeit less stable than retrieval error across the range of values considered. Mean CLW-WS crosstalk error increased for WS greater than 15 m s$^{-1}$ but remained less than roughly
FIG. 2.3. Plots of RMSD as a function of EIA for the simulated retrievals of CLW (top-left; red line), WV (top-right; green line), and WS (bottom; blue line). The RMSD values at each EIA were averaged across all GDAS simulations. In the RMSD calculations, the “predicted” CLW, WV, and WS values were those from Eqs. 6–8, and the “observed” values were the geophysical parameters from the GDAS profiles.

0.05 mm, and standard deviation was around 0.1 mm. CLW-WV crosstalk error was more chaotic, with mean error nearly unbiased for WV around 0 mm but increasing in magnitude to approximately 0.1 mm for WV around 60 mm, and standard deviation increased from about 0.05 mm for WV near 0 mm to more than 0.15 mm for WV greater than 30 mm. This may have been due to increased attenuation from higher WV concentration resulting in higher CLW-WV crosstalk error (e.g., Liebe 1985; Liebe 1989). Mean CLW-SST crosstalk error gradually increased from about -0.02 to 0.04 mm across the 0–30°C range of SST considered, and standard deviation remained about 0.1–
FIG. 2.4. Plots of cloud liquid water retrieval error (top-left) and the cloud liquid water crosstalk errors with 10-m wind speed (top-right), water vapor (bottom-left), and sea-surface temperature (bottom-right) calculated using Eqs. 6–8, with simulated AMPR $T_b$ as input values, compared to geophysical values obtained from the NCEP GDAS atmospheric profiles. The red dotted line in each plot indicates the mean error averaged across all EIAs, and the dashed lines in each plot indicate one standard deviation in the error across all EIAs.

0.15 mm. Deviations in CLW retrieval and crosstalk values may have also occurred due to inaccuracies in the assumptions present in Eq. 6 when attempting to model CLW based on $T_b$ values, as well as residual uncertainties from the radiative models discussed in section 2.3. The average CLW retrieval RMSD was 0.11 mm and median retrieval MedAD was $2.26 \times 10^{-2}$ mm.

Next, WV retrieval and crosstalk errors are shown in Fig. 2.5, while WV retrieval RMSD as a function of EIA can be found in Fig. 2.3. As with CLW, WV RMSD reached
FIG. 2.5. As in Fig. 2.4, except these plots are of water vapor retrieval error (top-left) and the water vapor crosstalk errors with cloud liquid water (top-right), 10-m wind speed (bottom-left), and sea-surface temperature (bottom-right).

a maximum of 1.32 mm around nadir, but decreased exponentially with increasing EIA, likely owing to increasing differences in horizontally and vertically polarized $T_b$. In general, WV error trends in Fig. 2.5 were less chaotic than those for CLW in Fig. 2.4, which may have been due to higher CLW values being less common in the GDAS data, leading to chaotic error trends as a result of lower sample size. Mean WV retrieval error was around 0 mm for WV values less than 30 mm, with a standard deviation of approximately 1 mm. Mean error was slightly negative between 30 and 50 mm, reaching peak magnitude of 0.5 mm around 40 mm, with a standard deviation around 1.5 mm. Once WV increased above 50 mm, retrieval error increased considerably, with mean
error of 1 mm and standard deviation around 1.5 mm for WV of 60 mm and greater. This
trend of WV error magnitude increasing with increasing WV is similar to CLW-WV
crosstalk error increasing with increasing WV in Fig. 2.4, possibly due to increased
attenuation. Further examining Fig. 2.5, WV crosstalk errors with CLW, WS, and SST
were all fairly stable, with near-zero mean WV crosstalk error and standard deviation of
1–1.5 mm across the range of values considered. Average WV retrieval RMSD was
1.28 mm and median retrieval MedAD was 0.22 mm, indicating that Eq. 7 provided fairly
accurate WV estimation.

Lastly, WS retrieval and crosstalk errors are presented in Fig. 2.6, while WS
RMSD as a function of EIA can be found in Fig. 2.3. From Fig. 2.3, similar to CLW and
WV, the WS RMSD reached a maximum around 1.41 m s\(^{-1}\) at nadir before decreasing
with increasing EIA. It can be noted that the range of WS RMSD in Fig. 2.3 is the largest
of the three parameters, owing largely to its dependence on differences between
horizontally and vertically polarized \(T_b\) (e.g., Wilheit and Chang 1980). In Fig. 2.6, as
with WV, WS crosstalk errors with WV, CLW, and SST are fairly uniform, with a mean
around 0 m s\(^{-1}\) and standard deviation of approximately 1 m s\(^{-1}\) across the range of WV,
CLW, and SST examined; the main exception is WS-SST crosstalk error for SST around
0–3°C, where mean error varies from about -0.8 to -0.4 m s\(^{-1}\). Thus, as with Eq. 7 for
WV, Eq. 8 provided a fairly accurate estimate of 10-m WS across a variety of WV, CLW,
and SST. Mean WS retrieval error fluctuates from negative values for WS less than
5 m s\(^{-1}\), to positive values for WS between 5 and 15 m s\(^{-1}\), and slightly negative for WS
greater than 15 m s\(^{-1}\). Underestimation of WS less than 5 m s\(^{-1}\) makes sense physically,
since the 10.7-GHz AMPR channel is sensitive to SST and surface disturbances (e.g.,
FIG. 2.6. As in Fig. 2.4, except these plots are of 10-m wind speed retrieval error (top-left) and the 10-m wind speed crosstalk errors with water vapor (top-right), cloud liquid water (bottom-left), and sea-surface temperature (bottom-right).

Wentz and Meissner 2007; Hong and Shin 2013), but wind speeds less than 5 m s\(^{-1}\) may not disturb the ocean surface considerably from a flat calm, yielding little response in 10.7-GHz \(T_b\) and, thus, wind speed underestimation (e.g., Wilheit and Chang 1980; Hong and Shin 2013). Conversely, the slight overestimation in WS between 5 and 15 m s\(^{-1}\) may be due to greater surface disturbance leading to greater response in the 10.7-GHz channel than expected. Other sources of error exist, such as use of multi-linear regression for the non-linear relation between WS and \(T_b\) (Wilheit and Chang 1980), residual uncertainty from the radiative models in section 2.3, and other inaccuracies in the assumed structure of Eq. 8 for deriving WS from \(T_b\). However, WS retrieval errors are
relatively low under most conditions in Fig. 2.6, with mean error magnitude and standard deviation less than 1 m s\(^{-1}\) for WS between 3 and 19 m s\(^{-1}\). The average WS retrieval RMSD was 1.11 m s\(^{-1}\), and median retrieval MedAD was 0.55 m s\(^{-1}\).

2.5 Methods for Testing the Retrieval Equations

This section details how Eqs. 6–8 were applied to data collected during OLYMPEX/RADEX. In this study, the performances of these equations were evaluated over four ER-2 flights: 23 Nov, 24 Nov, 10 Dec, and 13 Dec 2015. As part of the analysis, a \(T_b\) calibration was firstly performed for all AMPR data collected during these flights to remove biases resulting from the four quantities in Eq. 4. After deconvolving the raw AMPR \(T_b\) data into pure horizontally and vertically polarized \(T_b\), following Yang et al. (2013), any departure in observed \(T_b\) from a predicted value during each flight constituted a \(T_b\) bias via the relation

\[
T_{b,\text{bias}} = T_{b,\text{observed}} - T_{b,\text{simulated}}.
\]

In the analysis, the \(T_{b,\text{observed}}\) values were those obtained during the ER-2 flights, while the \(T_{b,\text{simulated}}\) values were calculated from GDAS data points throughout each AMPR flight path using Eq. 5. However, unlike the calculations discussed in section 2.3, the SST and wind speed values from the GDAS profiles were utilized throughout each flight to provide an accurate representation of the atmospheric conditions during the flights (i.e., SST and wind speed were not randomly selected when calibrating the AMPR \(T_b\) data).

The \(T_b\) at each scan angle was averaged for each case to evaluate mean bias in horizontally and vertically polarized deconvolved \(T_b\), seen in Fig. 2.7. In general, observed horizontally polarized AMPR \(T_b\) tends to be more positively biased while
vertically polarized $T_b$ tends to be more negatively biased. To account for this, the $T_b$ bias resulting from all four parameters in Eq. 4 was calculated for each scan angle during each flight (not shown), and the resulting values were subtracted from the $T_b$ biases in Fig. 2.7, yielding the values in Fig. 2.8. This $T_b$ bias correction was applied to all AMPR scans during the four case dates prior to their use in the geophysical retrievals. In each OLYMPEX/RADEX case, AMPR surface pixels were masked from the retrieval analyses if they were over land, based on visual inspection of the data, or if the ER-2 roll magnitude was greater than 1°.

The performances of Eqs. 6–8 were analyzed via two methods: comparisons with an independent retrieval method and comparisons with $in situ$ observations. In this study, the selected independent retrieval method was a one-dimensional variational (1DVAR) technique (Duncan and Kummerow 2016). While the 1DVAR presented in Duncan and Kummerow (2016) was developed for use with conically scanning microwave radiometers, such as the GPM Microwave Imager (GMI), Schulte and Kummerow (2019) and Schulte et al. (2020) demonstrated how 1DVAR is also applicable to cross-track-scanning radiometers. The 1DVAR is an optimal estimation technique, based on Bayes’ theorem, used to determine the state of the atmosphere based on input $T_b$ values and an input $a priori$ vector of state variables, which is needed to constrain the solution (Duncan and Kummerow 2016; Schulte and Kummerow 2019; Schulte et al. 2020). This inverse method of estimating the atmosphere’s state from input $T_b$, as shown and discussed in Schulte and Kummerow (2019) and Schulte et al. (2020) based on the full mathematical description provided in Rodgers (2000), may be expressed mathematically as

$$y = f(x,b) + \varepsilon,$$  \hspace{1cm} (11)
FIG 2.7. Plots of the mean bias in observed AMPR $T_b$ from four ER-2 flights: 23 Nov (black lines), 24 Nov (red lines), 10 Dec (green lines), and 13 Dec 2015 (blue lines) compared to the simulated AMPR $T_b$ values from the GDAS profiles throughout each flight. The four panels illustrate the mean $T_b$ bias at 10.7 (top-left), 19.35 (top-right), 37.1 (bottom-left), and 85.5 GHz (bottom-right) frequencies for the four case study dates. The x-axes denote AMPR’s scan angle, with negative (positive) values located on the left (right) half of the scan swath, and 0° corresponding to nadir. Within each plot, the solid lines represent the deconvolved vertically polarized $T_b$ at that frequency, while the dashed lines represent the deconvolved horizontally polarized $T_b$ values. All $T_b$ biases were calculated using Eq. 10. Adapted from Biswas et al. (2017).

where $y$ is a vector containing the observed $T_b$ values, $x$ is a vector containing the atmospheric parameters of interest, $b$ is a vector containing additional atmospheric features that influence $T_b$ but are not directly of interest, $f$ is a forward model that relates the atmospheric variables to the observed $T_b$ values, and $\varepsilon$ represents errors caused by noise, uncertainties in the atmospheric parameters contained within vector $b$, etc.

1DVAR provides a method by which the vector $x$ in Eq. 11 can be determined via inversion using the observed $T_b$ values, $a priori$ information about the state of the atmosphere, and an estimation of errors. Using these inputs, 1DVAR calculates a cost function that considers the difference between a given solution (from Eq. 11) and the $a$
priori state, as well as the difference between the observed $T_b$ values and the $T_b$ values predicted by the forward model in Eq. 11:

$$\Phi = (x - x_a)^T S_a^{-1} (x - x_a) + [y - f(x,b)]^T S_y^{-1} [y - f(x,b)],$$

(12)

where $x_a$ is the vector containing the a priori information, $S_a$ is the error covariance matrix for the a priori, and $S_y$ is the error covariance matrix for uncertainties in the forward model and the $T_b$ observations (Duncan and Kummerow 2016; Schulte and Kummerow 2019; Schulte et al. 2020). Using Newton’s method and assuming the error distribution is Gaussian, Eq. 12 is solved iteratively until the gradient in $\Phi$ with respect to $x$ reaches a minimum, at which point 1DVAR has converged on a solution (i.e., CLW, WV, and WS herein) based on the input $T_b$ values (Duncan and Kummerow 2016).

In this study, the values of $y$ in Eq. 11 were the observed $T_b$ values at the four AMPR frequencies collected during the selected OLYMPEX/RADEX flights, and the
vector $x$ included CLW, WV, and SST. The *a priori* state of the atmosphere was provided using Goddard Earth Observing System Model, Version 5 (GEOS-5) data from around the time and location of the selected ER-2 flight path. With these inputs, 1DVAR was used to compute CLW, WV, and WS for the same cases and AMPR pixels as Eqs. 6–8. In Eqs. 7 and 8, the median SST, calculated from the GDAS data points along the ER-2 flight path for the selected case, was used; median SST was chosen based on an empirical analysis (not shown) that indicated slightly improved agreement between 1DVAR and Eqs. 7 and 8 compared to using mean SST. For qualitative comparisons between the two methods, retrieved values throughout each ER-2 flight were visualized using 2-D histograms for all non-masked pixels. For quantitative comparisons, MedAD between the two retrieval methods was calculated for all pixels via Eq. 9, as was RMSD, where the values from Eqs. 6–8 were used as “predicted” for the given geophysical parameter and 1DVAR’s retrieval for the same pixel and geophysical parameter was “observed”.

Similar to Cecil and Biswas (2017), WS calculated using Eq. 8 was also compared with 10-m winds calculated using dropsonde data from the Advanced Vertical Atmospheric Profiling System (AVAPS; Hock and Young 2017), which was flown on the NASA DC-8 aircraft during OLYMPEX/RADEX (Houze *et al.* 2017). WV calculated using Eq. 7 was also compared with total precipitable water (TPW) calculated from AVAPS. CLW comparisons were not made herein due to the potential for very high spatial and temporal CLW variability, but are examined in chapter 3 using a separate dataset. Following Uhlhorn *et al.* (2007), if AVAPS data were available below 500 m AGL but unavailable below 150 m AGL, 10-m wind speed was calculated via
\[ WS_{10} = 0.8 \cdot \overline{WS_{0,500}}, \]  

(13)

where \( WS_{10} \) is 10-m wind speed, and \( \overline{WS_{0,500}} \) is mean AVAPS-measured wind speed between 500 m AGL and the surface. If AVAPS data were available below 150 m AGL, 10-m wind speed was calculated using

\[ WS_{10} = \overline{WS_{0,150}} \cdot \left[ 1.0314 - 4.071 \times 10^{-3}(z) + 2.465 \times 10^{-5}(z^2) - 5.445 \times 10^{-8}(z^3) \right], \]  

(14)

where \( \overline{WS_{0,150}} \) is mean AVAPS-measured wind speed between 150 m AGL and the surface, and \( z \) is mean height AGL for wind data recorded below 150 m AGL. While these equations were derived to increase accuracy in radiometer estimations of 10-m hurricane-force winds (e.g., \( > 50 \) m s\(^{-1}\)), they are applicable at lower wind speeds (Uhlhorn et al. 2007). TPW was calculated using all AVAPS levels where dew point and pressure data were available via

\[ TPW = \frac{1}{\rho g} \int_{p_1}^{p_2} r(p) \, dp \approx \frac{1}{\rho g} \left( r(p_2) + \frac{r(p_1)}{2} \right) (p_2 - p_1), \]  

(15)

where \( \rho \) is density of liquid water, \( g \) is gravitational acceleration, and \( r(p) \) is mixing ratio integrated between pressure levels \( p_1 \) and \( p_2 \) (AMS 2019).

Since AVAPS and AMPR were flown on separate aircraft, there were spatial and temporal differences in their datasets. Thus, WV and WS calculated using AVAPS and AMPR data were compared at two times for each available dropsonde: at the time of AVAPS minimum (min.) height (i.e., spatial offset between AMPR and AVAPS) and when AMPR passed over the location where AVAPS reached its min. height (i.e., temporal offset between AMPR and AVAPS). Dropsondes launched when the ER-2 was not over the ocean were not considered. When comparing AMPR and AVAPS, all AMPR scans during the time period of approximately 5 minutes before the time of
interest (*i.e.*, the time of AVAPS min. height or the time AMPR passed over the AVAPS min. height location) to 5 minutes after the time of interest were used to calculate an average AMPR-derived WV and WS. In cases where the ER-2 was over land or turning when AVAPS reached min. height, AMPR scans during the time period of 15 to 5 minutes before AVAPS min. height were used instead. These 10-minute periods were selected to provide larger-scale averages of WV and WS around the time of interest to account for spatial and temporal offsets between the two datasets. The dates, times, and locations of all dropsondes analyzed are shown in Table 2.1. MedAD (Eq. 9) was used to compare WV and WS from AVAPS and AMPR data, with AVAPS used as the “observed” quantity. MedAD was utilized in this study due to the small AVAPS sample size, as will be discussed in section 2.6. Since outliers will heavily influence RMSD in a small sample size, MedAD better represents the calculated AMPR-AVAPS deviations.

2.6 Retrieval Equations Applied to OLYMPEX/RADEX Cases

This section illustrates the utility of Eqs. 6–8 when applied to AMPR data from OLYMPEX/RADEX. Comparisons with independent methods (*i.e.*, 1DVAR and AVAPS) are presented. For brevity, in-depth examples will be shown for two OLYMPEX/RADEX cases, but the performances of Eqs. 6–8 compared to 1DVAR and AVAPS will be summarized for all four dates examined.

2.6.1 Case 1: 24 November 2015

The 24 Nov 2015 case featured a relatively high-amplitude positively tilted trough axis over the study region, with 1000-hPa geopotential heights as low as 30 m within the
TABLE 2.1. The date of each AVAPS dropsonde analyzed in this study, the time the dropsonde reached its minimum (min.) recorded height, the latitude and longitude (Lat, Lon) location of the dropsonde at its minimum recorded height, the (Lat, Lon) location of AMPR at the time the dropsonde reached its min. height, and the time AMPR passed over the AVAPS min. height (Lat, Lon) location. A star in the fourth column indicates that the listed (Lat, Lon) represents AMPR’s location 10 minutes before AVAPS reached min. height in cases where AMPR was over land at the actual time of AVAPS min. height.

<table>
<thead>
<tr>
<th>Date</th>
<th>Time of AVAPS Min. Height (UTC)</th>
<th>AVAPS (Lat, Lon) at Min. Height (deg)</th>
<th>AMPR (Lat, Lon) at AVAPS Min. Height (deg)</th>
<th>Time AMPR Reached AVAPS Min. Height (Lat, Lon) (UTC)</th>
</tr>
</thead>
<tbody>
<tr>
<td>20151123</td>
<td>1741:13</td>
<td>(47.2021, -126.639)</td>
<td>(47.7750, -126.151)</td>
<td>1757:53</td>
</tr>
<tr>
<td>20151123</td>
<td>1921:08</td>
<td>(48.1935, -125.960)</td>
<td>(47.5564, -125.057)</td>
<td>1702:43</td>
</tr>
<tr>
<td>20151123</td>
<td>1936:25</td>
<td>(47.6687, -124.999)</td>
<td>(48.0426, -125.933)</td>
<td>1942:25</td>
</tr>
<tr>
<td>20151123</td>
<td>1948:48</td>
<td>(48.1808, -125.908)</td>
<td>(47.9237, -125.549)*</td>
<td>1906:53</td>
</tr>
<tr>
<td>20151124</td>
<td>1803:57</td>
<td>(47.1599, -125.640)</td>
<td>(46.6466, -126.472)</td>
<td>2036:05</td>
</tr>
<tr>
<td>20151124</td>
<td>1813:57</td>
<td>(46.8343, -126.884)</td>
<td>(47.0178, -126.447)</td>
<td>1801:19</td>
</tr>
<tr>
<td>20151210</td>
<td>1734:17</td>
<td>(46.8752, -125.143)</td>
<td>(47.0766, -124.946)*</td>
<td>1829:58</td>
</tr>
<tr>
<td>20151210</td>
<td>1841:48</td>
<td>(46.8564, -125.194)</td>
<td>(47.0697, -124.961)*</td>
<td>1721:56</td>
</tr>
<tr>
<td>20151213</td>
<td>1721:08</td>
<td>(47.7733, -125.627)</td>
<td>(47.5862, -125.275)*</td>
<td>1751:36</td>
</tr>
</tbody>
</table>

low-pressure center that propagated through the study region less than 6 hours before the ER-2 flight (UWYO 2019). Deconvolved horizontally polarized AMPR $T_b$ from a portion of the flight can be found in Fig. 2.9, during which time some weak precipitation can be observed (e.g., around 2020–2033 UTC), allowing for equation testing in clear air and weak precipitation. To further support the inference of precipitation, data from the ground-based NASA S-band Dual-polarimetric (NPOL) radar (Wolff et al. 2017) were examined. Two NPOL range-height-indicator (RHI) scans through the region of precipitation sampled by AMPR around 2020–2033 UTC are presented in Fig. 2.10, which were created using the Python ARM Radar Toolkit (Helmus and Collis 2016). Regions of equivalent radar reflectivity factor ($Z_{H}$) > 30 dBZ can be seen at the lowest elevation angles of both RHI scans, especially at 224° azimuth, which are indicative of moderate rainfall rates at S-band (e.g., Straka et al. 2000).
FIG 2.9. Deconvolved horizontally polarized AMPR brightness temperatures at the frequencies 10.7 (top plots), 19.35 (second-from-top plots), 37.1 (middle plots), and 85.5 GHz (second-from-bottom plots) during portions of the ER-2 flights on 24 Nov 2015 (left) and 13 Dec 2015 (right). AMPR scan positions are shown on the y-axis in the top four plots for each date, with scan position 25 corresponding to nadir. Aircraft roll angle is presented in the bottom plot for each date.

Using the 24 Nov data in Fig. 2.9, CLW, WV, and WS calculated via Eqs. 6, 7, and 8, respectively, can be found in Fig. 2.11. From Fig. 2.11, it can be seen further that weak precipitation was present amongst clear air, such as 2031 UTC when CLW and WV increased to roughly 0.5 mm and 20 mm, respectively. However, in most pixels, CLW and WV are less than 0.5 mm and 20 mm, respectively. WS is slightly less uniform, ranging from near 0 to 15 m s\(^{-1}\) throughout Fig. 2.11. For the same flight portion, 1DVAR retrievals of CLW, WV, and WS can also be seen in Fig. 2.11. Based on Fig. 2.11, both retrieval methods yielded similar CLW and WV. As discussed below, wind speeds obtained with 1DVAR were a few m s\(^{-1}\) higher than those obtained via Eq. 8, especially around 1930–2000 UTC, likely owing to differences in how each method performs its retrievals (i.e., multi-linear regression vs inversion). In addition, some pixels were masked by 1DVAR but unmasked for the new retrieval equations; this may have been caused by regions of supercooled cloud water co-located with snow (i.e.,
FIG. 2.10. Range-Height-Indicator (RHI) scans of equivalent radar reflectivity factor ($Z_{th}$) measured by the NPOL radar at 2022 UTC on 24 Nov 2015. The two panels represent RHI scans along azimuth angles 224° (top) and 227° (bottom).

precipitation-size ice crystal aggregates), which are not accounted for in 1DVAR, causing 1DVAR to not reach convergence on a solution for these pixels. However, both methods yielded nearly the same CLW and WV and similar WS across these AMPR scans, including capturing the slantwise area of higher WS around 2005–2017 UTC, indicating good agreement and their ability to perform these retrievals.

To further examine CLW, WV, and WS retrieved using Eqs. 6–8 compared to 1DVAR, 2-D histograms were made between the two methods for all quality-controlled AMPR pixels on 24 Nov. These histograms are presented in Fig. 2.12, where it can be seen that a majority of CLW and WV data points fall near their respective 1-to-1 ratio lines, indicating good agreement. Most WS data points are shifted above the 1-to-1 ratio line, indicating that Eq. 8’s WS values were generally lower than those calculated via 1DVAR, likely due to use of multi-linear regression rather than inversion. As will be discussed further for the next case, breakpoints along the WS y-axis in Fig. 2.12 (e.g., at
FIG 2.11. Values of cloud liquid water (top plots), water vapor (second-from-top plots), and 10-m wind speed (second-from-bottom plots) calculated using the new geophysical retrieval equations (left) and 1DVAR (right) from the AMPR data on 24 Nov 2015 shown in Fig. 2.9. The ER-2 aircraft roll angle is shown in the bottom plots. For CLW retrievals via the new equation, pixels with CLW < 0 mm after applying the $T_b$ bias corrections have been masked.

15 m s$^{-1}$) were also likely caused by pixels where 1DVAR’s solution remained close to the *a priori* value due to the presence of precipitation.

To summarize Eqs. 6–8 compared to 1DVAR, RMSD and MedAD values were calculated for all quality-controlled AMPR pixels from the four OLYMPEX/RADEX cases, as seen in Table 2.2. 24 Nov had CLW, WV, and WS RMSD values of approximately $3.78 \times 10^{-2}$ mm, 1.63 mm, and 1.69 m s$^{-1}$, respectively, and MedAD values of approximately $1.83 \times 10^{-2}$ mm, 1.03 mm, and 0.76 m s$^{-1}$, respectively. The relatively low RMSD and MedAD values match the good agreement between the two methods in Fig. 2.12, especially for CLW. These results indicate that geophysical values calculated via Eqs. 6–8 correlate well with 1DVAR, which matches the results of Wentz (1997) and suggests that both methods can be useful in these retrievals.

Next, for comparison with *in situ* observations, WV and WS calculated via Eqs. 7 and 8 were compared with values calculated using AVAPS dropsondes from the same case dates. As described in section 2.5, 10-m AVAPS wind speed was calculated using
TABLE 2.2. An overview of the median RMSD values between 1DVAR and the new retrieval equations for CLW, WV, and WS (second through fourth columns, respectively) during each of the four OLYMPEX/RADEX case dates analyzed in this study, as well as the median MedAD values between these retrieval methods for CLW, WV, and WS (fifth through seventh columns, respectively) and the correlation coefficient (CC) values between the two retrieval methods for CLW, WV, and WS (eighth through tenth columns, respectively). The median value for each statistic calculated across the four case dates is presented in the bottom row. All values were calculated across all quality-controlled AMPR data for each case.

<table>
<thead>
<tr>
<th>Date</th>
<th>CLW RMSD (mm)</th>
<th>WV RMSD (mm)</th>
<th>WS RMSD (m s⁻¹)</th>
<th>CLW MedAD (mm)</th>
<th>WV MedAD (mm)</th>
<th>WS MedAD (m s⁻¹)</th>
<th>CLW CC</th>
<th>WV CC</th>
<th>WS CC</th>
</tr>
</thead>
<tbody>
<tr>
<td>20151123</td>
<td>1.01 x 10⁻¹</td>
<td>2.47</td>
<td>2.64</td>
<td>2.72 x 10⁻²</td>
<td>1.40</td>
<td>2.13</td>
<td>0.76</td>
<td>0.50</td>
<td>0.85</td>
</tr>
<tr>
<td>20151124</td>
<td>3.78 x 10⁻²</td>
<td>1.63</td>
<td>1.69</td>
<td>1.83 x 10⁻²</td>
<td>1.03</td>
<td>0.76</td>
<td>0.89</td>
<td>0.77</td>
<td>0.86</td>
</tr>
<tr>
<td>20151210</td>
<td>2.55 x 10⁻¹</td>
<td>2.26</td>
<td>4.68</td>
<td>5.67 x 10⁻²</td>
<td>1.26</td>
<td>4.12</td>
<td>0.76</td>
<td>0.81</td>
<td>-0.27</td>
</tr>
<tr>
<td>20151213</td>
<td>9.81 x 10⁻²</td>
<td>1.73</td>
<td>2.06</td>
<td>3.03 x 10⁻²</td>
<td>1.02</td>
<td>1.51</td>
<td>0.76</td>
<td>0.66</td>
<td>0.23</td>
</tr>
<tr>
<td>Median</td>
<td>9.95 x 10⁻²</td>
<td>2.00</td>
<td>2.35</td>
<td>2.88 x 10⁻²</td>
<td>1.14</td>
<td>1.82</td>
<td>0.76</td>
<td>0.72</td>
<td>0.54</td>
</tr>
</tbody>
</table>

Eqs. 13 or 14 and AVAPS water vapor was calculated using Eq. 15. The differences between AVAPS and AMPR wind speed and water vapor around the time AVAPS reached min. height and around the time AMPR passed over the AVAPS min. height location can be found in Fig. 2.13. From the left plots in Fig. 2.13, the wind speed difference was less than 1 m s⁻¹ for both available dropsondes on 24 Nov, indicating excellent agreement between AMPR-derived WS and in situ observations. AMPR and AVAPS were approximately 40 and 80 km apart at the min. height times, so this agreement indicates similar wind speeds at the AMPR and AVAPS locations and lack of isolated convection impacting the WS comparisons, as discussed in the next case. Likewise, the water vapor differences less than 2.5 mm indicate good agreement between AMPR and AVAPS, which is near the highest precision observed by Wilheit and Chang (1980) of 1.5 mm, and matches the fairly uniform water vapor seen in Fig. 2.11. However, the AMPR-AVAPS spatial offset likely contributed to the differences seen in Fig. 2.13, which is a limitation of comparing data from instruments on separate aircraft.
FIG 2.12. Two-dimensional histograms comparing cloud liquid water (top plots), water vapor (middle plots), and 10-m wind speed (bottom plots) calculated using the new retrieval equations (x-axes) and 1DVAR (y-axes) for all quality-controlled AMPR pixels during the ER-2 flights on 24 Nov 2015 (left) and 13 Dec 2015 (right). The red dashed line in each plot indicates a one-to-one ratio between the two retrieval methods.

From the right plots in Fig. 2.13, it can be seen further that AVAPS observations agreed very well with AMPR-derived values; wind speed differences were less than 0.5 m s\(^{-1}\) when AMPR passed over the AVAPS min. height location for both 24 Nov dropsondes. This is most trustworthy for the 1759 UTC dropsonde, since AMPR passed
FIG 2.13. Absolute values of the differences between 10-m wind speed (top plots) calculated using the new retrieval equations and calculated from AVAPS data for the four case study dates: 23 Nov (red bars), 24 Nov (green bars), 10 Dec (blue bars), and 13 Dec 2015 (purple bars). Absolute values of the differences between water vapor via the same calculations are presented in the center plots. These calculations were performed at two times: at the time the AVAPS dropsonde reached its minimum recorded height (left plots) and at the time AMPR passed over the location where AVAPS recorded its minimum height (right plots).

The bottom-left plot is of spatial offsets between AMPR and AVAPS at the time AVAPS reached its minimum recorded height, while the bottom-right plot is of temporal offsets between when AVAPS reached its minimum recorded height and when AMPR passed over the location where AVAPS recorded its minimum height; these spatial and temporal offsets are based on the values seen in Table 2.1. The x-axis in each plot represents the launch times of the respective AVAPS dropsondes. Wind speed and water vapor values calculated using AMPR data were averaged over a time period of approximately 10 minutes, as described in the main text.

over the min. height location less than 15 minutes prior. However, the 0.11 m s⁻¹ difference for the 1749 UTC dropsonde is interesting considering the time difference greater than 2.5 hours, which was the highest temporal offset in this study. Water vapor agreement was also strong, with differences of approximately 2 mm or less. As previously noted, these good agreements likely resulted in part from the large amount of clear-air data minimizing any contamination from isolated convection. Additionally, despite the presence of a low-pressure center off the coast of Oregon at 1800 UTC, surface pressure gradients over the domain were relatively low at 1800 UTC (UWYO 2019). This likely contributed to the relatively strong agreements in water vapor and wind speed despite the spatial and temporal offsets, especially for the 2.5-hour offset for the 1749 UTC dropsonde.
2.6.2 Case 2: 13 December 2015

During the 13 Dec 2015 case, similar to 24 Nov, a relatively high-amplitude, positively tilted trough propagated through the study region; however, the low-pressure center was deeper for 13 Dec, with 1000-hPa geopotential heights as low as -90 m at 1200 UTC (UWYO 2019). Horizontally polarized deconvolved \( T_b \) during part of the ER-2 flight can be found in Fig. 2.9, where scattered convection is indicated by local maxima in \( T_b \) throughout the flight path. This contrasts the light precipitation on 24 Nov and allowed for the retrievals to be tested within stronger convection.

CLW, WV, and WS retrieved using Eqs. 6–8 and the 13 Dec data in Fig. 2.9 are presented in Fig. 2.14, where the \( T_b \) maxima are reflected by local CLW and WV maxima. The 13 Dec WS pattern was more complex than 24 Nov, indicated by local WS maxima up to 20 m s\(^{-1}\); the higher mean background wind on 13 Dec compared to 24 Nov may have resulted from the more intense low-pressure center and associated slightly higher pressure gradient on 13 Dec and the passage of a cold front on this day (WPC 2019). The slight bow-like appearance to some local WS maxima (e.g., around 1940 UTC) is interesting. Given the location of this WS maximum near the local CLW and WV maxima, it is possible that this feature, as well as other small-scale WS variability, is a gust front associated with a convective storm (Biswas et al. 2017). This is noteworthy as it indicates the potential to estimate gust front wind speeds using AMPR data and Eq. 8.

To demonstrate that these high-WS areas are not strictly due to rain impact on the AMPR signal, CLW data were masked for CLW > 0.01 mm, as seen in Fig. 2.15. Since the WS maxima fall outside areas where CLW is greater than 0.01 mm, they avoid
FIG 2.14. As in Fig. 2.11, but for a portion of the ER-2 flight on 13 Dec 2015.

potential rain contamination. Although all AMPR data are sampled at a 0.6-km cross-track resolution, the raw resolution of the 10.7- and 19.35-GHz data is 2.8 km. To avoid potential influences of CLW on WS estimations (e.g., O’Dell et al. 2008), all WS data within ±5 pixels, or roughly 3 km, of a CLW > 0.01 mm observation were masked in the along-track and across-track dimensions. These results are presented in the second panel of Fig. 2.15, where it can be seen that WS maxima fall outside of these potentially cloud-affected pixels, further suggesting that these WS signatures are not the result of a data artifact. In addition, NPOL RHIs through convective storms around the same time as these AMPR analyses are presented in Fig. 2.16, wherein the radial velocity ($V_r$) values within the precipitating storms stand out against the background wind field and support the inference of gust fronts. Gust front analysis with AMPR data needs further examination in future work, but the potential exists for these analyses to be performed.

Retrieved CLW, WV, and WS via 1DVAR on 13 Dec are also shown in Fig. 2.14, where it can be seen that 1DVAR did not yield output for several pixels where $T_b$ values were relatively high. The precipitation implied by these high $T_b$ values, especially at 10.7 and 19.35 GHz, is not accounted for in 1DVAR’s forward model. 1DVAR’s cost
FIG 2.15. A plot (top) of 10-m wind speeds for AMPR pixels where the cloud liquid water was ≤ 0.01 mm (red colorbar) and cloud liquid water values for AMPR pixels where the cloud liquid water was > 0.01 mm (blue colorbar) during the portion of the 13 Dec 2015 ER-2 flight shown in Fig. 2.14. The same data are presented in a geolocated manner in the bottom image. The second-from-top plot is of cloud liquid water values (blue colorbar) for all pixels within ±5 pixels in the cross-track or along-track directions of any pixel with a cloud liquid water value > 0.01 mm, with wind speed values (red colorbar) plotted for all pixels that did not meet these criteria. The third-from-top plot is of ER-2 aircraft roll angle over the same time period.
FIG. 2.16. Range-Height-Indicator (RHI) scans of equivalent radar reflectivity factor ($Z_{RH}$; top-left) and radial velocity ($V_r$; top-right) measured by the NPOL radar at 1920 UTC on 13 Dec 2015 along an azimuth angle of 210°. The bottom two panels represent the same parameters measured along an RHI azimuth angle of 216° at 1920 UTC.

function increased nearer the $T_b$ maxima (not shown), and eventually 1DVAR failed to reach a solution within these $T_b$ maxima. This resulted in 1DVAR’s WS reverting back to the GEOS-5 a priori throughout Fig. 2.14, especially near the $T_b$ maxima, which, as seen in Fig. 2.12 and discussed below, resulted in 1DVAR not capturing the smaller-scale WS variability that was captured by Eq. 8. However, background wind speed is similar between the two methods. Mean WV is also similar between 1DVAR and Eq. 7, and local CLW maxima are captured by both methods.

These results indicate fair agreement between both methods, but to further examine the correlation between 1DVAR and Eqs. 6–8, 2-D histograms across all
quality-controlled AMPR pixels on 13 Dec are shown in Fig. 2.12. From Fig. 2.12, the methods agreed well for CLW and WV for most pixels; however, the WS pattern is interesting. WS less than 15 m s\(^{-1}\) saw similar behavior as on 24 Nov, where Eq. 8 yielded values a few m s\(^{-1}\) less than 1DVAR; however, for WS greater than the artifact around 15 m s\(^{-1}\) on the y-axis, Eq. 8 yielded higher WS (by 10 m s\(^{-1}\) in some cases) for many pixels. This is reflected in a low correlation coefficient of 0.23 between Eq. 8 and 1DVAR WS on 13 Dec, shown in Table 2.2. A significant reason for this difference arises from Eq. 8 attempting to retrieve even in pixels where precipitation is present, whereas 1DVAR typically fails to reach convergence in these pixels and will revert back to its \textit{a priori} value in nearby pixels. Wind speeds in the GEOS-5 data nearest the 13 Dec 2015 flight path were around 15–18 m s\(^{-1}\) (not shown). Thus, in pixels where 1DVAR reverted back to its background values on this day (\textit{e.g.}, around precipitation), the wind speed values output from 1DVAR were around 15–18 m s\(^{-1}\), which seemed to yield the high data concentration around these values on the y-axis in Fig. 2.12. The retrievals attempted by Eq. 8 near precipitation regions likely contributed to its higher WS compared to 1DVAR in Fig. 2.12, in addition to any differences resulting from use of multi-linear regression versus 1DVAR’s inversion method.

To evaluate other sources that may contribute to the breakpoint and data clustering around 15 m s\(^{-1}\), several analyses were performed using pixels where 1DVAR reached convergence (not shown) targeting three hypotheses for this behavior: 1) 1DVAR encountered difficulties calculating WS near nadir due to little difference in the horizontally and vertically polarized \(T_b\) data; 2) high CLW values (\textit{i.e.}, near, but largely not within, precipitation) also caused 1DVAR to revert back to the GEOS-5 \textit{a priori} wind
speeds; 3) 1DVAR reached convergence on WS values that were different from the a priori value, but with a cost function ($\chi^2$) value that was unacceptably large (i.e., $\chi^2 > 10$; Duncan and Kummerow 2016), causing 1DVAR to use the a priori wind speeds. For each of these analyses, different levels of masking were individually applied to the retrieved WS from 1DVAR and Eq. 8; all data with EIA < 10, 20, 30, and 40 degrees were masked, as were all pixels with retrieved CLW > 1 x $10^{-4}$, 5 x $10^{-4}$, 1 x $10^{-3}$, and 5 x $10^{-3}$ mm, and all pixels with a 1DVAR $\chi^2$ value > 0.5, 1, 5, and 10. In all cases, the data clustering around 15–18 m s$^{-1}$ on the 1DVAR axis persisted, as did the 15 m s$^{-1}$ breakpoint. However, as fewer and fewer pixels nearer the middle of the scan swath were considered via the increased EIA masking levels, the WS data points converged on the 1-to-1 ratio line between the two retrieval methods, indicating greater agreement between the methods, despite the continued breakpoint. The same phenomenon was observed when applying $\chi^2$ masks, with data points converging on the 1-to-1 ratio line more strongly when masking $\chi^2 > 0.5$ compared to $\chi^2 > 10$. This convergence was not observed for the different levels of CLW masking. Thus, while masking the AMPR data based on EIA and 1DVAR’s $\chi^2$ value indicated improved agreement between the retrieval methods, they did not fully explain the 15 m s$^{-1}$ breakpoint along 1DVAR’s axis or the clustering of 1DVAR WS around 15–18 m s$^{-1}$. This is especially interesting for the increased $\chi^2$ values, as it indicates that, while precipitation influenced 1DVAR’s retrievals, the increases in $\chi^2$ nearer precipitation do not seem to fully explain the 15 m s$^{-1}$ breakpoint.

Apart from this WS behavior, Eqs. 6–8 and 1DVAR agreed fairly well. This is further reflected in the CLW, WV, and WS RMSD values of 9.81 x $10^{-2}$ mm, 1.73 mm,
and 2.06 m s\(^{-1}\), respectively, in Table 2.2 and MedAD values of 3.03 \(\times 10^{-2}\) mm, 1.02 mm, and 1.51 m s\(^{-1}\), respectively. These values agree with the deviations from the 1-to-1 ratio line in Fig. 2.12 and indicate fairly good agreement between the retrieval methods. To compare AMPR-derived WV and WS with \textit{in situ} observations on 13 Dec, an AVAPS data analysis similar to 24 Nov was performed. However, only one dropsonde was available during the ER-2 flight on 13 Dec. Comparing AVAPS and AMPR at the time of AVAPS min. height, seen in Fig. 2.13, the wind speed and water vapor differences were roughly 1.93 m s\(^{-1}\) and 1.36 mm, respectively, which is good agreement despite AMPR being more than 30 km from AVAPS. Examining AMPR’s overpass of the AVAPS min. height location, which took place 30 min later as seen in Fig. 2.13, the wind speed and water vapor differences were about 1.54 m s\(^{-1}\) and 1.01 mm, respectively, which is very good agreement with a relatively low temporal offset. In general, WV and WS from Eqs. 7 and 8 compared well with AVAPS on 13 Dec, which likely resulted from surface pressure gradients that were only slightly greater than those on 24 Nov (UWYO 2019).

\textbf{2.6.3 Summary of All Case Dates}

The overall performances of Eqs. 6–8 compared to 1DVAR are indicated by the RMSD and MedAD values in Table 2.2. The median MedAD values calculated across the four cases were 2.88 \(\times 10^{-2}\) mm, 1.14 mm, and 1.82 m s\(^{-1}\) for CLW, WV, and WS, respectively, while median RMSD values were 9.95 \(\times 10^{-2}\) mm, 2.00 mm, and 2.35 m s\(^{-1}\), respectively. These results indicate excellent agreement between the new retrieval equations and 1DVAR overall. CLW yielded the lowest uncertainty of all three
parameters, as in Wentz (1997), with RMSD and MedAD values on the same order of magnitude as observed in Wentz (1997) and Wilheit and Chang (1980). The WV RMSD of 2.0 mm is approximately 0.6 mm lower than that noted in Duncan and Kummerow (2016), but is approximately 0.8 mm higher than the RMSD noted in Wentz (1997). In addition, the overall WS MedAD of 1.82 m s\(^{-1}\) is 0.18 m s\(^{-1}\) below the baseline uncertainty of 2.0 m s\(^{-1}\) noted in past wind retrieval studies (e.g., Wentz and Meissner 2007; Ruf et al. 2019), while the WS RMSD of 2.35 m s\(^{-1}\) falls slightly above this baseline uncertainty. However, WS RMSD increased from use of a one-step retrieval equation compared to the two-step approach used in past studies, such as the RMSD of 1.0–1.8 m s\(^{-1}\) noted in Wilheit and Chang (1980). These factors indicate improvements in geophysical retrievals that are possible with these new equations when applied to AMPR data. A notable feature in Table 2.2 is the relatively high MedAD and RMSD values for WS on 10 Dec, which are nearly double the second-highest values. As with 13 Dec, a high amount of precipitation was present on 10 Dec, which impacted the retrievals due to the differences in how both methods handle precipitation.

The overall performance of Eqs. 7 and 8 compared to AVAPS can be found in Fig. 2.13. The MedAD for WV and WS calculated across all nine dropsondes was 2.10 mm and 1.15 m s\(^{-1}\), respectively, at the time AVAPS reached min. height, while MedAD at the location of AVAPS min. height was 1.80 mm and 1.53 m s\(^{-1}\), respectively. Averaging these data pairs yields a mean MedAD of 1.95 mm for WV and 1.34 m s\(^{-1}\) for WS. Cases where AMPR-derived and AVAPS-derived WV and WS differed considerably (e.g., 1906 and 1921 UTC on 23 Nov) were influenced by isolated convection (not shown); in some cases, AMPR was over an isolated convective storm
while AVAPS was dropped away from the storm, thus impacting WV and WS comparisons at AVAPS min. height time. Similarly, in some cases (including the two aforementioned 23 Nov dropsondes), a convective storm developed around the AVAPS min. height location during the time between AVAPS reaching min. height and the ER-2 passing over that location.

Furthermore, a cold front extended through the center of the study domain at 1800 UTC on 23 Nov (UWYO 2019), which likely contributed to the considerable differences in the dropsondes around 1900 UTC on this day. The surface pressure gradients were relatively low away from the cold front on 23 Nov, which may have contributed to relatively good agreements in the 1726 and 1934 UTC dropsondes. Conversely, pressure gradients were significantly higher on 10 Dec in association with an intense low-pressure center northwest of Washington (UWYO 2019), which likely contributed to the differences seen over time for the 1827 UTC dropsonde in Fig. 2.13. This suggests that dropsondes with a relatively high spatial and/or temporal offset on 23 Nov and 10 Dec, such as those at 1726, 1906, and 1921 UTC on 23 Nov and 1827 UTC on 10 Dec, may present a less-reliable comparison for water vapor and wind speed validations compared to those with a high spatial and/or temporal offset on 24 Nov and 13 Dec. Therefore, the 1934 UTC dropsonde on 23 Nov and the 1720 UTC dropsonde on 10 Dec present the most reliable comparisons for these two case dates. These are example limitations of comparing data from instruments flown on different aircraft.

Despite these temporal and spatial offset issues, both sets of MedAD indicate that WV and WS from Eqs. 7 and 8 agreed fairly strongly with AVAPS. Both WS MedAD values are less than the 2.0 m s$^{-1}$ baseline uncertainty noted in Wentz and Meissner
(2007) and Ruf et al. (2019), and are similar to the WS RMSD of 1.2 m s$^{-1}$ and 0.9 m s$^{-1}$ reported in Duncan and Kummerow (2016) and Wentz (1997), respectively. Likewise, the WV MedAD values are 0.5–0.8 mm lower than the 2.6- mm RMSD noted in Duncan and Kummerow (2016), but are 0.6–0.9 mm higher than the 1.2- mm RMSD presented in Wentz (1997).

### 2.7 Summary of AMPR Retrievals and OLYMPEX/RADEX Analyses

The purpose of this chapter was to provide an overview of AMPR’s polarimetric upgrades and calibrations, and to demonstrate the ability to obtain realistic CLW, WV, and WS from AMPR data via three new geophysical retrieval equations. AMPR T$_b$ simulated from NCEP GDAS atmospheric profiles were used to train the retrieval equations, and their performances were initially tested against geophysical data from the GDAS profiles. The new retrieval equations were then applied to AMPR T$_b$ recorded during four OLYMPEX/RADEX cases, the results of which were compared to the same parameters calculated via 1DVAR for the same AMPR dataset. Mixed-polarization AMPR T$_b$ were deconvolved into true horizontally and vertically polarized T$_b$, and biases in observed T$_b$ were removed prior to using the new equations with OLYMPEX/RADEX data. WV and WS calculated via the new retrieval equations were also compared with in situ AVAPS dropsonde data.

Comparing retrievals from simulated AMPR T$_b$ against the GDAS profiles yielded nearly unbiased mean CLW retrieval error across the range of CLW values examined, with minimal crosstalk errors apart from WV greater than 30 mm. Mean WV retrieval error was near 0 mm for WV less than 50 mm, and crosstalk errors were around
0 mm. Retrieval error for WS fluctuated from negative values for WS less than 5 and greater than 15 m s\(^{-1}\) to positive values for WS between 5 and 15 m s\(^{-1}\), though mean error magnitude was less than 1 m s\(^{-1}\) for WS between 3 and 19 m s\(^{-1}\). WS crosstalk errors were nearly unbiased apart from SST between 0 and 3°C, where the mean error magnitude was still less than 1 m s\(^{-1}\). Mean retrieval RMSD for CLW, WV, and WS were 0.11 mm, 1.28 mm, and 1.11 m s\(^{-1}\), respectively, while the respective median MedAD values were 2.26 x 10\(^{-2}\) mm, 0.22 mm, and 0.55 m s\(^{-1}\).

Using AMPR \(T_b\) data collected during OLYMPEX/RADEX to calculate the geophysical parameters, there was relatively strong agreement between the new equations and 1DVAR. Both methods were able to retrieve similar values in clear air, while the new retrieval equation attempted to retrieve in light precipitation on 24 Nov and in stronger convection on 13 Dec, whereas 1DVAR does not converge on a solution in precipitation regions, leading to differences in the retrievals around areas of precipitation. The new WS equation captured small-scale WS variability on 13 Dec that may have been associated with gust fronts, which demonstrates its utility in analyzing smaller-scale features. Median RMSD for CLW, WV, and WS across the four cases was 9.95 x 10\(^{-2}\) mm, 2.00 mm, and 2.35 m s\(^{-1}\), respectively, while median MedAD was 2.88 x 10\(^{-2}\) mm, 1.14 mm, and 1.82 m s\(^{-1}\), respectively.

When comparing WV and WS from the new equations with AVAPS, two approaches were taken: 1) compare both datasets at the time of AVAPS min. height, regardless of spatial offset, and 2) compare both datasets at the location of AVAPS min. height, regardless of temporal offset. For the nine available dropsondes, the WV MedAD was 2.10 and 1.80 mm at the time and location of AVAPS min. height, respectively,
while the respective WS MedAD values were 1.15 and 1.53 m s\(^{-1}\), resulting in an overall average MedAD of 1.95 mm (1.34 m s\(^{-1}\)) for WV (WS). These results indicate that the new WV and WS equations compared well with in situ observations, despite the spatial and temporal offsets between the instruments and associated errors resulting from isolated convection and pressure gradients.

The results herein are promising, but future work must further analyze the new retrieval equations. One avenue for future work could expand the analysis of WS artifacts observed in some of the 1DVAR data to consider other error sources. Training an artificial neural network to perform the geophysical retrievals would be interesting, given the potential for deviations in the multi-linear regression equations where the assumed relation between the retrieved property and the T\(_b\) values does not wholly represent their true relation. Additional OLYMPEX/RADEX cases should be tested and compared with the results herein, which will be performed as the entire OLYMPEX/RADEX dataset is reprocessed using Eqs. 6–8. Comparing CLW with in situ data may be challenging, but would provide useful validation. Testing the equations on AMPR datasets from other field campaigns, such as the recent Cloud, Aerosol and Monsoon Processes Philippines Experiment (CAMP\(^2\)Ex) as discussed in detail throughout chapters 3 and 4, where AMPR and AVAPS were flown on the same aircraft, and Investigation of Microphysics and Precipitation for Atlantic Coast-Threatening Snowstorms (IMPACTS), will also be beneficial to examine their performances in other climate regions throughout the world.
Chapter 3. Applying Retrievals in the Tropics: CAMP$^2$Ex

This chapter details the expansion of AMPR’s geophysical retrievals from the wintertime midlatitudes to the summertime tropics. Alongside this change in geography and climate regime, AMPR’s WV and WS retrievals are tested using a much larger dropsonde dataset than employed in chapter 2. Modifications to the CLW retrievals for use in the maritime tropics are detailed, and the updated CLW retrievals are validated against independent measurements. With these rigorously tested and validated retrievals available across CAMP$^2$Ex, they are applied to analyses that address CAMP$^2$Ex science questions. This chapter will focus primarily on the science applications of AMPR’s retrievals specifically, with additional datasets used for comparison with these retrievals to address CAMP$^2$Ex science goals. A more direct analysis of aerosol and environmental impacts on convection is presented in chapter 4, and additional datasets are investigated both alongside and independently of AMPR’s retrievals therein. It should also be noted that the units used in association with AMPR’s CLW and WV retrievals were changed from mm in Amiot et al. (2021) (i.e., chapter 2) to kg m$^{-2}$ in chapters 3 and 4; however, values expressed in either unit are equivalent (e.g., 1 mm = 1 kg m$^{-2}$). While the peer-reviewed manuscript comprising this chapter has not yet been submitted, some text throughout includes wording suggestions from its co-authors.
3.1 CAMP$^2$Ex, background, and purpose

NASA’s Cloud, Aerosol and Monsoon Processes Philippines Experiment (CAMP$^2$Ex) focuses on interactions between aerosols, radiation, and clouds in the maritime tropics (Reid et al. 2023). CAMP$^2$Ex’s field phase occurred from 20 August – 10 October 2019, with NASA’s P-3B Orion (P-3) aircraft operating out of Clark International Airport. The P-3 conducted 19 research science flights (SFs) covering a range of geographical, synoptic, mesoscale, aerosol, and radiation conditions (Reid et al. 2023). AMPR was the primary instrument used in this study, while other P-3 instruments, as discussed in section 3.2, included: AVAPS, Research Scanning Polarimeter (RSP), and Airborne Precipitation and cloud Radar 3rd Generation (APR-3).

Past studies have used airborne and spaceborne microwave radiometers to obtain geophysical information. For example, Smith et al. (1994), Kummerow et al. (1996), and Leppert and Cecil (2015) used radiometer data to characterize hydrometeor properties (e.g., phase and size). Other works (e.g., Wilheit and Chang 1980; Wentz 1997; Wentz and Spencer 1998; Wentz and Meissner 2000; Hong and Shin 2013) have obtained integrated and near-surface atmospheric properties, such as cloud liquid water path (CLW) and total precipitable water vapor (WV), and near-surface parameters, such as 10-m wind speed (WS), using brightness temperature ($T_b$) combinations from multiple frequencies. These geophysical retrievals are based on properties of emitted and scattered radiation at different microwave frequencies (e.g., Wentz and Meissner 2000). To assess accuracies of these retrievals, output values have been compared with modeling (e.g., Yeh et al. 1990; Zhou et al. 2013; Hwang et al. 2019) and observational (e.g.,
Wentz 1997; McGrath and Hewison 2001; Cecil and Biswas 2017) data, which have demonstrated the considerable accuracy of microwave atmospheric retrievals.

Additional studies (e.g., Spencer et al. 1994; Hood et al. 2006; Amiot et al. 2021) have applied underlying theories of these retrievals to AMPR data across multiple field campaigns, with multi-linear regression equations for CLW, WV, and WS retrievals derived and tested for OLYMPEX/RADEX (Houze et al. 2017) in Amiot et al. (2021), as discussed in chapter 2. AMPR’s 10.7-GHz channel is least susceptible to atmospheric attenuation and is ideal for observing near-surface properties like WS (Spencer et al. 1994; Hood et al. 2006; Amiot et al. 2021). The 19.35-, 37.1-, and 85.5-GHz channels are increasingly influenced by precipitation, clouds, and even water vapor, making them useful in diagnosing integrated parameters like CLW and WV (Spencer et al. 1994; Hood et al. 2006; Amiot et al. 2021).

Others have used satellite-retrieved cloud optical thickness (COT) and droplet effective radius ($r_e$) near cloud top to derive integrated CLW, assuming an adiabatic in-cloud vertical profile associated with cloud droplet growth after cloud condensation nuclei are activated near the non-precipitating cloud base (e.g., Bennartz 2007; Miller et al. 2016). This assumed profile implies that cloud liquid water content (LWC) should scale linearly with cloud-top height (CTH), and that vertical integration to obtain CLW will cause CLW to be proportional to (CTH)$^2$ (e.g., Bennartz 2007; Miller et al. 2016). Therefore, based on this adiabatic assumption, it was hypothesized that an (AMPR CLW) $\propto$ (CTH)$^2$ trend would be present in non-precipitating clouds during CAMP$^2$Ex. However, several cloud processes may not be fully represented by this assumption, such as entrainment and subsequent evaporation of cloud droplets, changes
in cloud droplet size distribution due to collision-coalescence, high CLW gradients present near cloud edges, and variations in both shortwave radiation and in-cloud vertical velocities (Bennartz 2007; Miller et al. 2016).

In the maritime tropics, ocean-surface fluxes result in a water-vapor-rich boundary layer (e.g., Tompkins 2001). Though heavily dependent on synoptic patterns and mesoscale features (e.g., cold pools), these fluxes are driven by mean wind speeds around 6–8 m s⁻¹ (West and Smith 2021). Since the tropical environmental 0°C level is often around 5 km AMSL (e.g., Zipser and LeMone 1980; Fierro et al. 2012), which is generally higher than in the midlatitudes (e.g., Harris et al. 2000), the warm-phase layer is generally deeper in tropical clouds (e.g., Mülmenstädt et al. 2015). As a result, tropical cumulus-type clouds may have considerable CLW (e.g., >0.1 kg m⁻²; O’Dell et al. 2008), though clouds with low CLW (i.e., near 0 kg m⁻²) are most common, with observed frequency decreasing in an exponential manner as CLW increases (e.g., Ackerman 1959; Oh et al. 2018). Enhanced latent heat release during condensation can occur over a greater warm-layer depth, which may intensify tropical convection (all else being equal; e.g., Tomassini 2020). During dissipation, these stronger convective storms may produce local WS enhancements due to the formation of a cold pool (e.g., Lucas et al. 2000).

Thus, it was hypothesized that AMPR’s CLW and WS retrievals would be directly related to the height of the environmental 0°C level.

The purposes of this study are twofold: 1) expand AMPR’s geophysical retrievals, including testing and validation, to maritime tropical environments; and 2) demonstrate the utility of these retrievals in addressing science questions of airborne field campaigns such as CAMP²Ex. While this study was performed using AMPR, the results have wider
applications, such as quantifying CLW, WV, and WS from spaceborne platforms with similar frequencies as AMPR. This includes past [e.g., Tropical Rainfall Measuring Mission (TRMM) Microwave Imager (TMI; Simpson et al. 1988; Kummerow et al. 1998)], present [e.g., Global Precipitation Measurement (GPM) Microwave Imager (GMI; Skofronick-Jackson et al. 2017)], and future [e.g., Atmosphere Observing System (AOS) mission (AOS 2022)] platforms. The specific science questions addressed herein are:

1) What trends are present in AMPR’s tropical geophysical retrievals, and how do they compare with expectations based on prior studies?

2) What information can AMPR’s cloud liquid water (CLW) retrievals provide about cloud and precipitation processes?

3) What relations can be found between AMPR’s retrievals and dropsonde data on a flight-by-flight basis, and what are their physical explanations?

An overview of data and methods is provided in section 3.2, discussion of AMPR’s updated retrievals can be found in section 3.3 with examples of applications to CAMP²Ex science questions in section 3.4, section 3.5 concludes with a summary and future work, and Appendix A provides additional details of AMPR’s CLW validation.

3.2 Data and Methods Used in Expanding AMPR’s Retrievals

3.2.1 Data

As outlined in chapters 1 and 2, AMPR is a total-power radiometer that scans cross-track ±45° beneath an aircraft, providing mixed-polarization $T_b$ at four central frequencies/channels: 10.7, 19.35, 37.1, and 85.5 GHz (Spencer et al. 1994). With dual
orthogonal receivers at each channel, pure horizontally (H) and vertically (V) polarized \( T_b \) can be computed across AMPR’s entire scan swath via dual-polarization deconvolution (Amiot et al. 2021). These H and V polarized \( T_b \) are the foundation for AMPR-based geophysical retrievals of CLW, WV, and WS via multi-linear regression equations (Amiot et al. 2021). AMPR typically records data in 50 cross-track pixels per scan, with pixel footprint resolution varying with aircraft altitude (Spencer et al. 1994).

Prior to CAMP\(^2\)Ex, a new AMPR radome was designed, constructed, and tested before integration on the P-3 (Lang et al. 2021). This flat-surface radome was custom built out of Rexolite (http://www.rexolite.com) by ProSensing Inc. to be P-3 compatible and optimized for AMPR’s frequencies, but may have an insertion loss up to ~1 dB that varies with incidence angle and frequency. This loss occasionally affected AMPR-measured radiometric counts, which translated to artifacts in \( T_b \) and geophysical retrievals that were mitigated during data quality control (QC).

All data used herein were from CAMP\(^2\)Ex SFs 05–19 (i.e., 04 Sept – 05 Oct 2019); AMPR was inoperable during SF 01, and SFs 02–04 were excluded due to un-optimized settings for some of AMPR’s gains and offsets (Lang et al. 2021). An AMPR pixel was QC masked if: 1) P-3 pitch or roll magnitude was \( \geq 2^\circ \), 2) AMPR was in its nadir-stare mode, 3) P-3 GPS altitude was < 3 km, 4) the given AMPR scan included at least one pixel over land, and/or 5) precipitation was present within the given pixel based on 37.1- and 85.5-GHz \( T_b \) thresholds (Lang et al. 2021). Aircraft pitch/roll magnitudes \( \geq 2^\circ \) were masked due to the regression coefficients in AMPR’s retrieval equations being tied to Earth Incidence Angle (EIA) rather than scan angle, and were derived assuming level flight. Similarly, coefficients at most EIAs become invalid when AMPR stares
nadir. AMPR’s cold calibration target is cooled using ambient air from around the aircraft, which occasionally provided insufficient cooling during CAMP²Ex within warmer air at lower altitudes, leading to data quality issues for altitudes < 3 km AGL. Since AMPR’s CLW, WV, and WS retrievals are based on atmospheric properties over an ocean background, they become invalid over land and/or within precipitation; however, while not used herein, other AMPR retrievals are possible over land (e.g., ice water path; McMurdie et al. 2022). P-3 altitude ranged from roughly 3–7 km AGL herein, yielding approximate AMPR cross-track footprint resolutions of 94–220 m.

WV and WS derived from 2-Hz AVAPS data (Freeman et al. 2020) were gathered from Aknan and Chen (2020) and compared with AMPR’s retrievals throughout a given dropsonde’s descent; therefore, dropsondes were discarded if no AMPR data were available during their descent (e.g., repeated significant aircraft maneuvers). Of the 154 dropsondes available during SFs 05–19 (Vömel et al. 2020), only three were removed due to lack of corresponding AMPR data, one (two) from SF 08 (SF 14). Another seven dropsondes were removed during QC (e.g., unavailable near-surface wind data), leaving 144 total dropsondes for use in this analysis. AVAPS pressure, temperature, relative humidity, and horizontal wind uncertainties are ±0.5 hPa, ±0.2°C, ±3%, and ±0.5 m s⁻¹, respectively (Freeman et al. 2020).

APR-3 scans in a 50° cross-track swath beneath the P-3, ±25° from nadir, at three frequencies: 13.4 GHz (Ku band), 35.6 GHz (Ka band), and 94 GHz (W band; Durden et al. 2020). These data were also obtained from Aknan and Chen (2020). While data were available from all three channels during CAMP²Ex, only Ku- and Ka-band equivalent radar reflectivity factor \((Z_{HH})\) and Doppler velocity \((V_d)\) were used for the analyses herein.
This decision was made due to: 1) W-band’s susceptibility to significant attenuation; and 2) the majority of W-band data throughout CAMP²Ex being solely nadir, rather than cross-track (albeit, this was more of an issue in chapter 4 than in this chapter). The vertical resolution of each range gate during CAMP²Ex was approximately 30 m. $Z_H$ data were not corrected for attenuation effects nor were $V_r$ data corrected for aircraft motion. Applying a simple stepped $Z_H$ correction through several APR-3 columns did not improve statistics discussed herein (not shown). However, attenuation was most significant in precipitation regions, which were largely masked during validation following Lang et al. (2021), and $V_r$ was only used in a limited manner during QC. Despite this, some precipitation regions were likely missed by the $T_b$-threshold method used to flag precipitation (Lang et al. 2021). APR-3 data files from Aknan and Chen (2020) were excluded if they only contained W-band data, and an additional 10 files, each covering 3–14 min of flight time, were manually removed due to high levels of observed noise: one each from SFs 09, 17, and 18, two from SF 11, and five from SF 15.

RSP data were also gathered from Aknan and Chen (2020). RSP (Cairns et al. 1999) measures I, Q, and U Stokes parameters at nine wavelengths in the visible and shortwave infrared spectrums. RSP scans 105° along track at a rate of about 0.86 seconds, during which observations at more than 100 viewing angles are collected (van Diedenhoven et al. 2020b). RSP’s spatial resolution is about 14 mrad, or roughly 10–100 m depending on distance between the aircraft and cloud top. The multi-angle polarimetric data at a wavelength near 865 nm are used to infer the cloud-top droplet size distribution effective radius and effective variance (Alexandrov et al. 2012). Cloud optical thickness is inferred from the nadir observations near 865 nm (van Diedenhoven
et al. 2020a). Cloud top heights used in section 3.4 are inferred using a multi-angle parallax method and have an estimated accuracy of $<$ 500 m (Sinclair et al. 2017). Additional details regarding RSP QC are provided below.

### 3.2.2 Methods

The retrieval equations from Amiot et al. (2021) were first applied to AMPR’s CAMP$^2$Ex dataset (Fig. 3.1). During the segment of SF 09 presented in Fig. 3.1, WV appears relatively uniform with reasonable values for the maritime tropics (i.e., background of $\sim$50 kg m$^{-2}$; second row), but two issues are apparent in the other retrievals: 1) CLW around 0.1 kg m$^{-2}$ in clear-air regions (first row), and 2) cross-track WS stripes (third row). These features appeared during a majority of the field campaign, and it was concluded that CLW and WS retrievals would require updates for CAMP$^2$Ex. The high clear-air CLW likely resulted from high water vapor in the tropics, while cross-track variations in WS (and possibly CLW) were likely caused by the new AMPR radome used during CAMP$^2$Ex. As discussed later, WS stripes were corrected by applying simple offsets to the Amiot et al. (2021) equation results, while an entirely new CLW equation was derived and used to obtain initial CLW estimates before an offset was applied to all AMPR pixels within a given SF. An in-depth discussion of CLW corrections is provided in Appendix A, and bulk AMPR retrieval statistics were computed across SFs 05–19.

For comparisons with AMPR-derived WV and WS, total precipitable water and 10-m wind speed were calculated from the 144 dropsondes following the equations from AMS (2019) and Uhlhorn et al. (2007) referenced in Amiot et al. (2021). Since AMPR
FIG. 3.1. Strip charts (i.e., top-view time series) of AMPR data and retrievals from approximately 0308–0314 UTC during SF 09. Time is presented on all x axes while AMPR’s cross-track scan position is shown on the top seven y axes, with nadir corresponding roughly to scan position 25. From top to bottom, the plots in each column are of: AMPR’s CLW, WV, and WS retrievals, deconvolved H polarized T$_b$ at 10.7, 19.35, 37.1, and 85.5 GHz, and the P-3 pitch and roll angles and altitude. The left column presents retrievals from direct application of the Amiot et al. (2021) equations, along with uncorrected T$_b$. The right column presents updated CLW via Eq. 19 and corrected WS via the values in Fig. 3.8, along with corrected T$_b$. WV retrievals are the same in both columns. An example of AMPR’s CAMP$^2$Ex precipitation flag can be seen in the WS retrievals around 0312:51 UTC in the right column. Retrievals have been masked in the 10 scan positions nearest the swath edges due to residual radome effects, and retrievals are masked around 0310 UTC due to P-3 roll angle exceeding the ±2° threshold, though T$_b$ are still shown.

and AVAPS were both on the P-3 during CAMP$^2$Ex, spatial and temporal offset issues encountered when they flew on separate aircraft during OLYMPEX/RADEX (Amiot et al. 2021) were not present. However, AMPR-derived WV and WS were averaged during the entirety of each dropsonde descent to reduce influences from noise and non-
precipitating clouds (Amiot et al. 2021). Percentage (absolute) differences between AMPR- and AVAPS-derived values were used to evaluate AMPR’s WV (WS) retrievals, respectively, with AVAPS used as “truth.” Additional AVAPS parameters, such as 0°C level height, were also computed and compared with AMPR retrievals.

Validating AMPR’s CLW retrievals proved more challenging than the WV and WS retrievals, given difficulties in correctly associating a single cloud target within an AMPR overpass to in situ observations. As a result, independent CLW values were calculated using APR-3 and RSP data. For consistency in viewing angle and signal paths through the atmosphere, only nadir data were used from these instruments. After QC, which is detailed in Appendix A, each APR-3 scan was matched with the nearest AMPR scan. In each nadir column, two LWC values were calculated in each range gate, one from Ku-band $Z_H$ following Hagen and Yuter (2003) and another from Ka-band $Z_H$ following Oh et al. (2018); these equations, respectively, are:

$$\text{LWC}_{Ku} \left( \text{g m}^{-3} \right) = 3.4 z^{4/7},$$

$$\text{LWC}_{Ka} \left( \text{g m}^{-3} \right) = \left( \frac{Z}{103.82} \right)^{1/1.08},$$

where $z$ is linear radar reflectivity (mm$^6$ m$^{-3}$). It should be noted that Eq. 16 was originally derived for use in regions of rain water, namely raindrops with diameter > 0.2 mm (Hagen and Yuter 2003); however, it was examined herein given the relative scarcity of $z$-LWC relationships in the literature compared to relationships between $z$ and rain rate (i.e., $z$-R relationships), as also noted in Hagen and Yuter (2003). Likewise, though Eq. 17 was also intended to retrieve LWC from raindrops, it offered the lowest errors (herein “deviations” or “differences”) of all equations in Oh et al. (2018) when compared with AMPR CLW (not shown), which may have been influenced by any rain
regions missed by AMPR’s precipitation flag as discussed later. It should also be noted that Eqs. 16 and 17 assume the absence of ice hydrometeors in their retrievals (Hagen and Yuter 2003; Oh et al. 2018). LWC values were integrated through their respective column to get CLW (expressed in kg m\(^{-2}\)). Once all CLW values were calculated during a given flight, the times associated with each APR-3 and AMPR scan were compared, and a column was only used in the final analysis if all three CLW observations were present concurrently (i.e., within approximately 2 seconds of each other, since the time between subsequent cross-track AMPR scans is generally 3–4 seconds; Lang et al. 2021).

Within this “trio” dataset, absolute deviation, percentage deviation, and biases were calculated from each column, wherein APR-3 CLW was considered “truth,” and bulk statistics were gathered.

A similar analysis was performed using RSP data to compute CLW following the methods of Bennartz (2007) and Miller et al. (2016):

\[
CLW \left( \text{g m}^{-2} \right) = \frac{5}{9} \cdot \rho_w \cdot \text{COT} \cdot r_e,
\]

(18)

where COT is cloud optical thickness, \(r_e\) is cloud-top effective radius, and \(\rho_w\) is the density of liquid water. Cloud reflectance reaches an asymptote at high optical thickness values, which may lead to unrealistically high retrieved COT values. Since RSP’s retrievals do not limit maximum COT, any COT greater than 100 units was manually set to 100 units to constrain CLW. Once CLW was obtained for each nadir observation, the nearest AMPR scan to each RSP scan was determined, and all concurrent AMPR CLW and RSP CLW observations during a given flight were used to calculate absolute deviation, percentage deviation, and bias. RSP-AMPR bulk statistics from SFs 05–19 were also determined.
3.3 AMPR’s Tropical Retrievals: Updates and Validation

This section presents CLW, WV, and WS retrievals in separate subsections. Each includes a discussion of the equation’s CAMP$^2$Ex update (if applicable) and validation against Global Data Assimilation System (GDAS; NCEP 2000) simulations and/or independent CAMP$^2$Ex data. Given its substantial update, additional details regarding CLW validation are provided in Appendix A. Some science applications are demonstrated in section 3.4.

3.3.1 Cloud Liquid Water

AMPR’s CLW retrieval underwent the largest transformation between OLYMPEX/RADEX and CAMP$^2$Ex. Applying AMPR’s original CLW equation from Amiot et al. (2021) (i.e., Eq. 6 in chapter 2) to CAMP$^2$Ex (e.g., SF 15; Fig. 3.2) resulted in clear-air CLW around 0.1–0.2 kg m$^{-2}$. Though the magnitude differed among SFs, all flights contained clear-air CLW values > 0 kg m$^{-2}$ throughout. This residual CLW was likely caused primarily by high tropical water vapor compared to the midlatitudes, which AMPR’s 85.5-GHz channel is particularly sensitive to. Since CLW is the only retrieval to utilize 85.5-GHz, it would be affected most strongly.

Sensitivity tests were performed by varying the CLW equation format (e.g., adding or removing elements and/or AMPR channels), and results were compared against the same 523,176 globally distributed GDAS profiles used in Amiot et al. (2021). The equation selected by virtue of having the lowest errors against GDAS simulations and least clear-air cross-track variance was:
FIG. 3.2. Strip charts of AMPR’s CLW retrievals from approximately 0349–0454 UTC during SF 15, with time presented on all x axes and AMPR’s scan positions on the top three y axes. The top panel presents the original retrievals using the Amiot et al. (2021) CLW equation, with the second (third) panel presenting the results of applying Eq. 19 to the same scene before (after) applying offset corrections. The bottom panel illustrates P-3 pitch and roll angles and altitude during the same flight segment.
\[ \text{CLW (kg m}^{-2}\text{)} = a_0 + a_1 T_{b19v} + a_2 T_{b19h} + a_3 \ln(290 - T_{b19v}) + a_4 \ln(290 - T_{b19h}) + a_5 T_{b37v} + a_6 T_{b37h} + a_7 \ln(290 - T_{b37v}) + a_8 \ln(290 - T_{b37h}) + a_9 T_{b85v} + a_{10} T_{b85h} + a_{11} \ln(295 - T_{b85v}) + a_{12} \ln(295 - T_{b85h}) + a_{13} \text{SST}, \]  

where, as in Amiot et al. (2021), “a” terms are regression coefficients derived for AMPR EIA every 0.2° (see Appendix A), \( T_{bxxh,v} \) represents \( T_b \) in Kelvin at xx-GHz frequency and H or V polarization, and SST is sea surface temperature in Kelvin. As seen in Fig. 3.2, applying Eq. 19 to the same AMPR data yielded lower clear-air CLW and much greater cross-track uniformity compared to the Amiot et al. (2021) equation. However, some residual clear-air CLW > 0 kg m\(^{-2}\) remained, the mitigation of which is discussed in Appendix A. In Eq. 19, a single SST was selected from the GDAS simulation and pixel nearest the middle of a given SF and applied uniformly to all AMPR pixels throughout the flight. As discussed in Amiot et al. (2021), this does not significantly influence the retrieved values, but provides a background to mitigate potential cross-track retrieval artifacts.

Comparing CLW simulations via Eq. 19 with GDAS values (Fig. 3.3), mean CLW retrieval and crosstalk errors remained nearly constant around 0 kg m\(^{-2}\) across the ranges of geophysical values tested, with most standard deviations < 2.5 x 10\(^{-2}\) kg m\(^{-2}\). This indicates excellent performance of Eq. 19 across various ocean-surface and atmospheric conditions. The root-mean-square deviation (RMSD) of Eq. 19’s retrieval error was 1.94 x 10\(^{-2}\) kg m\(^{-2}\), which is nearly an order of magnitude lower than the 0.11 kg m\(^{-2}\) retrieval RMSD in Amiot et al. (2021) and similar to the 2.0 x 10\(^{-2}\) kg m\(^{-2}\) RMSD noted in Wentz and Meissner (2000). The average retrieval error was 1.90 x 10\(^{-3}\) kg m\(^{-2}\), and mean crosstalk errors with WV, WS, and SST were very low, at 1.37 x 10\(^{-2}\),
FIG. 3.3. Plots of (top left) CLW retrieval error and crosstalk errors with (top right) WV, (bottom left) WS, and (bottom right) SST from comparing AMPR-derived values with those obtained from the 523,176 GDAS profiles. CLW, WV, and WS values were calculated using Eqs. 19, 5, and 6, respectively, while SST was obtained from the GDAS profiles. The red dotted line in each plot represents the mean value averaged across all EIAs, with the dashed black lines denoting ±1 standard deviation from the mean across all EIAs.

3.60 x 10^{-3}, and 4.79 x 10^{-4} kg m^{-2}, respectively. Based on its excellent simulation performances, Eq. 19 was tested using AMPR data from CAMP²Ex. Examining part of SF 09 (right column of Fig. 3.1), Eq. 19 yielded considerably lower residual clear-air CLW compared to the Amiot et al. (2021) equation, and cross-track variation was significantly reduced; therefore, Eq. 19 was selected as AMPR’s new CLW retrieval equation. However, as noted previously and discussed in Appendix A, slight residual clear-air CLW < 0.05 kg m^{-2} required additional correction. Other equations were examined during sensitivity testing, but they: a) did not compare as favorably with GDAS
as Eq. 19, b) had significant clear-air cross-track variability, and/or c) frequently yielded clear-air CLW < 0 kg m$^{-2}$.

Validating Eq. 19 with independent CAMP$^2$Ex observations proved challenging given differences in instrument operations and difficulties in correctly matching cloud measurements from multiple instruments. Comparisons against APR-3 Ka-band and RSP CLW are presented in this subsection, while details regarding APR-3 Ku-band validation can be found in Appendix A. This decision was made since Eq. 16 was not specifically designed for Ku-band data and its uncertainty due to random error may be as large as 176% (Hagen and Yuter 2003). Conversely, Eq. 17 was designed for Ka band, and the LWC calculation methods used by Oh et al. (2018) have uncertainties around 15% due to random error (Frisch et al. 1995; 1998). While cloud droplets would be expected to fall into the Rayleigh scattering regime at both frequencies, any residual raindrops missed by AMPR’s precipitation flag would significantly impact these z-LWC calculations. In addition, as noted in section 3.2, both equations were originally developed for raindrop retrievals, and were utilized herein based on the relative scarcity of z-LWC relationships in the literature as discussed in Hagen and Yuter (2003).

Examining AMPR CLW against Ka-band CLW “truth” values (Fig. 3.4), the overall median absolute deviation was found to be 0.432 kg m$^{-2}$, with a median percentage deviation around 85.7% and median bias of -7.02 x 10$^{-2}$ kg m$^{-2}$ (i.e., AMPR biased high relative to APR-3). While the focus is on median values as they are less sensitive to outliers, mean plots are included for greater transparency of the error statistics. Compared with Ku-band, median Ka-band percentage deviation and bias were considerably improved, with percentage deviation nearly two orders of magnitude lower
FIG. 3.4. Mean (left column) and median (right column) absolute deviations (top row), percentage deviations (second row), and biases (third row) between AMPR CLW and APR-3 Ka-band CLW for SFs 05–19. The bottom row presents the number of nadir data points used from each flight, while the red dashed line in each plot represents the overall mean (left column) or median (right column) value calculated across these SFs. Science flight dates on the x axis are listed according to takeoff date.

than those of Ku band. Ka band is more sensitive to cloud droplets than Ku band (all else being equal) and may have picked up on finer-scale in-cloud spatial variations that the Ku-band data did not fully resolve, in addition to Eq. 17’s design for Ka-band data. However, any residual raindrops missed by AMPR’s precipitation flag would have also contributed to the deviations at both frequencies, especially Ka band, as discussed below.

Likewise, the utilization of Eq. 17 might have contributed to the relatively large median absolute deviation, as it was originally intended for use with raindrops, despite it yielding the lowest errors of the equations from Oh et al. (2018) as mentioned in section 3.2. However, any residual raindrops in the masked dataset might have contributed to this “stronger” performance of Eq. 17 compared to the others in Oh et al. (2018). Median absolute deviation was similar between the two APR-3 bands and higher than
expectations given the $O(10^{-2} \text{ kg m}^2)$ uncertainty in the GDAS analysis. The high Ka-band median deviation of $\sim 3 \text{ kg m}^2$ in SF 08 (Fig. 3.4) was likely influenced by turbulence throughout this flight, which may have affected masking of near-surface range-/sidelobe effects. It can also be seen in Fig 3.4 that there were no coincident points during SFs 07, 17, and 18 when AMPR, Ku-band, and Ka-band CLW retrievals occurred.

To better compare AMPR CLW with Ka-band CLW, a 2D histogram can be found in Fig. 3.5. From this histogram, AMPR’s retrievals often produced higher CLW than APR-3’s retrievals. One explanation for this might be the influence of attenuation on $Z_H$, where AMPR derived an integrated CLW value using columnar information while the lack of $Z_H$ attenuation correction may have caused underestimation of LWC in range gates closer to the surface, leading to a lower column-integrated CLW value from the APR-3 data. It is also possible that some cloud droplets were too small to be captured by the Ka-band $Z_H$ data, given its sensitivity (i.e., minimum detectable $Z_H$) of -21 to -8 dBZ 3–7 km down-range from the radar (Dzambo et al. 2019), which may have contributed to cases where AMPR CLW was greater than Ka-band CLW. In addition, as mentioned previously, it should be noted that any raindrops missed by AMPR’s precipitation flag would greatly affect these comparisons. Examining the x axis in the left plot of Fig. 3.5, a total of 112 comparison data points had an AMPR CLW value > 1 kg m$^{-2}$, which has been used to isolate rainfall regions in past studies (e.g., Jiang and Zipser 2006). In other words, as much as roughly 12.5% of the validation dataset may have contained unmasked raindrops. Eq. 17’s original derivation for use with raindrops may have mitigated any apparent effects on the validation, but this also leads to some unreliable comparisons when focusing on cloud liquid water overall. As discussed below, this issue was largely
FIG. 3.5. Two-dimensional histograms, each with logarithmic axes, comparing AMPR CLW (x axes) with (left) APR-3 Ka-band CLW and (right) RSP CLW (y axes) for all unmasked nadir data points wherein (left) AMPR, Ku-band, and Ka-band observations and (right) AMPR and RSP observations were simultaneously available during SFs 05–19. The number of coincident observations (n) and Pearson correlation coefficient (r) are displayed in each plot. Red dashed lines denote a one-to-one ratio.

limited to the APR-3 analyses, and likely contributed to the resulting deviations between AMPR CLW and APR-3 CLW. Future work will revisit these calculations using updated masking and z-LWC calculations. With these limitations, a moderately weak correlation coefficient of 0.34 resulted between these datasets.

Absolute deviations from comparing AMPR CLW with RSP CLW (Fig. 3.6) were significantly lower than the APR-3 analyses, with a median around 8.08 x 10^{-2} kg m^{-2}. This is also less than the 0.11 kg m^{-2} RMSD noted from the GDAS analysis in Amiot et al. (2021). Given its finer 865-nm wavelength, it is likely that RSP was more sensitive to cloud droplets than the Ku- and Ka-band APR-3 data, which improved comparisons with AMPR CLW. RSP percentage deviations were similar to the Ka-band analysis, around 86.0%, while biases were improved with a median around -3.28 x 10^{-2} kg m^{-2}. The 1874 data points used in the RSP comparative analysis, as opposed to 870 for the APR-3 comparisons (Fig. 3.5), also increases the statistical significance of these results. It can also be seen in Fig. 3.5 that only 12 of the 1874 data points were associated with an
FIG. 3.6. As in Fig. 3.4, but for the comparison between AMPR CLW and RSP CLW. In each absolute deviation plot, the theoretical uncertainty in AMPR’s CLW retrievals from Amiot et al. (2021) has been marked by a black dashed line.

AMPR CLW value > 1 kg m\(^{-2}\), or roughly 6.4 x 10\(^{-3}\)% of the dataset. In addition to the finer sensitivity of RSP to the cloud droplets, this minimal influence from raindrops in the validation dataset strongly suggests that the AMPR-RSP comparisons are more indicative of the true error/deviation statistics for AMPR’s CLW retrievals. From Fig. 3.5, there was a stronger one-to-one relation between AMPR CLW and RSP CLW compared to the APR-3 analyses, leading to a moderate correlation of 0.42 and supporting the relatively low median deviations.

Additional in-depth descriptions of AMPR’s CLW validation methods are provided in Appendix A, including comparisons with APR-3 Ku-band CLW. Overall median absolute deviation, percentage deviation, and bias between CLW and Ku-band CLW were 0.410 kg m\(^{-2}\), 3.39 x 10\(^{-3}\)% and -0.155 kg m\(^{-2}\) (i.e., AMPR biased high relative to APR-3), respectively. These values are quite high, especially considering the 0.11 kg
m$^2$ theoretical uncertainty for AMPR’s prior CLW retrievals and the strong agreement between Eq. 19 and GDAS profiles. The high Ku-band deviations and bias magnitude may have been influenced by applying Eq. 16 to cloud drops given its original derivation for drop diameters > 0.2 mm (Hagen and Yuter 2003), the susceptibility of low CLW to high percentage deviation, and other limitations of the airborne validation methods discussed previously. In addition, the minimum detectable $Z_H$ for APR-3’s Ku-band frequency 3–7 km down range from the radar is approximately -6–6 dBZ (Dzambo et al. 2019), which likely resulted in cases where cloud droplets were too small and/or too low in concentration to be detected using Ku-band data. The aforementioned 112 data points with potential rain contamination in the radar analyses also likely contributed to the relatively high Ku-band deviations.

### 3.3.2 Water Vapor

AMPR’s WV retrieval method from Amiot et al. (2021) performed well against CAMP$^2$Ex in situ observations. Mean difference percentages between AMPR and AVAPS-derived WV for SFs 05–19 can be seen in Fig. 3.7, where all but two flights (SFs 08 and 10, likely due to a few residual noisy AMPR pixels and the presence of a mid-level dry layer in SF 08) had a mean difference < 10%, which is the target uncertainty (NASEM 2018). The overall mean difference of 8.27% was also less than this target. Further, initial cross-track WV stripe artifacts discussed in Amiot et al. (2021) did not appear during CAMP$^2$Ex (e.g., Fig. 3.1). For these reasons, AMPR’s WV retrieval equation (i.e., Eq. 7 in chapter 2) was left unchanged from Amiot et al. (2021).
FIG. 3.7. Bar plots of the percentage differences between AMPR and AVAPS WV retrievals (top) and the absolute differences between AMPR and AVAPS WS retrievals (bottom) during SFs 05–19. The mean AMPR-AVAPS percentage (absolute) differences in WV (WS) during OLYMPEX/RADEX from Amiot et al. (2021) are denoted by green dashed lines, while the black dashed line in each plot represents the target maximum uncertainty.
The relatively good agreement between Eq. 7 and AVAPS without modification is interesting considering the significant climatological differences between OLYMPEX/RADEX and CAMP$^2$Ex, the updates required for CLW and WS, and the AMPR channel overlap between WV and WS. Three main factors may be responsible for Eq. 7’s strong performance during CAMP$^2$Ex: 1) lack of 85.5-GHz $T_b$; 2) use of the single background SST from GDAS; and 3) all equation elements being linear or logarithmic, rather than exponential. As noted previously, AMPR’s 85.5-GHz channel is most strongly affected by high water vapor (e.g., as seen in CLW), but is not used in WV retrievals. This limits impacts of water vapor differences between OLYMPEX/RADEX and CAMP$^2$Ex. Further, despite a single SST being applied to every AMPR pixel uniformly across a given SF, the selected value may have helped scale the retrieved WV from lower values in OLYMPEX/RADEX to higher values in CAMP$^2$Ex. The statement regarding linear and logarithmic equation elements may explain why additional correction was needed for WS (next subsection), which uses exponential functions, but not WV. As also discussed below, WS stripe artifacts resulted from $T_b$ variation in subsequent scan positions, which would be amplified by exponential functions; this may explain why WS yielded artifacts while WV did not, despite using the same AMPR channels.

### 3.3.3 Wind Speed

Similar to CLW, but not as extensive, AMPR’s WS retrievals required updates for CAMP$^2$Ex. The original Amiot et al. (2021) equation (i.e., Eq. 8 in chapter 2) provided excellent agreement with in situ observations, with a mean AMPR-AVAPS difference of
1.81 m s\(^{-1}\) across SFs 05–19, which is less than the target uncertainty of 2 m s\(^{-1}\) (Wentz and Meissner 2007; Ruf et al. 2019). However, cross-track stripe artifacts were apparent in these WS retrievals (Fig. 3.1), which may be attributable to AMPR’s radome and associated transmission loss varying with incidence angle and frequency. To account for this, a median WS offset correction was calculated for each AMPR scan position across each SF (Fig. 3.8). In these calculations, the difference between WS in each pixel within an AMPR scan and the median WS from the same scan was calculated, and the overall median value of these differences was calculated for each of AMPR’s 50 scan positions across all scans during the SF. From Fig. 3.8, the vast majority of correction factors had magnitudes < 0.5 m s\(^{-1}\). The main exception was SF 18, which may have been affected by a large portion of the flight taking place over/near land. A similar cross-track trend occurred across the SFs (i.e., local maxima and minima at similar scan positions in Fig. 3.8), exemplifying some cross-track sensitivity of Eq. 8 which may have been amplified by AMPR’s radome. As a result, Eq. 8 may be applicable to other radiometers without correction, which could be explored in future work.

After adding the corrections in Fig. 3.8 to the raw WS retrievals, the resulting values were validated using the same 144 dropsondes employed in the WV validation. Compared to uncorrected WS, applying the corrections in Fig. 3.8 slightly improved the mean AMPR-AVAPS WS difference by 0.05 m s\(^{-1}\), yielding a CAMP\(^2\)Ex-average AMPR-AVAPS difference of 1.76 m s\(^{-1}\). This indicates excellent agreement and is less than the 2 m s\(^{-1}\) target uncertainty. Flight-by-flight WS differences can be seen in Fig. 3.7, where the mean difference was < 2 m s\(^{-1}\) in 11 flights. In addition, 40% of SFs
had a mean WS difference less than that observed by Amiot et al. (2021), further indicating the excellent performance of Eq. 8 + Fig. 3.8 during CAMP$^2$Ex.

### 3.4 Initial Science Applications in the Maritime Tropics

This section focuses on applications of AMPR’s retrievals in preliminary analyses related to the previously stated CAMP$^2$Ex science questions. An overview of AMPR’s bulk statistics is presented first, including implications for the maritime tropics. This is followed by discussion of AMPR CLW versus RSP-derived CTH, and a comparison of AMPR retrievals with some AVAPS-derived parameters.
3.4.1 Bulk AMPR CAMP²Ex Statistics

Bulk statistics for AMPR’s geophysical retrievals throughout SFs 05–19 can be found in Fig. 3.9, wherein median WV and WS are presented since slight residual $T_b$ enhancements near precipitation edges affected their mean values, while mean CLW is used since median CLW from SFs 05–19 was 0 kg m$^{-2}$. From Fig. 3.9, CLW retrievals reached a mode around 0 kg m$^{-2}$ and followed a relatively smooth decrease in histogram frequency as CLW increased, which matches expectations (e.g., Ackerman 1959; Oh et al. 2018). Mean AMPR CLW outside of precipitation-flagged regions was 0.07 kg m$^{-2}$, which is within the range of values expected in the maritime tropics (e.g., Greenwald et al. 1995). On a flight-by-flight basis (not shown), the minimum (maximum) mean CLW was $3.44 \times 10^{-3}$ kg m$^{-2}$ (0.223 kg m$^{-2}$) in SF 18 (SF 11).

Examining AMPR WV in Fig. 3.9, the histogram mode and median were approximately 50 kg m$^{-2}$ and 49.7 kg m$^{-2}$, respectively. These agree well with increased background WV expected in the maritime tropics compared to wintertime midlatitudes. For example, in retrievals shown from two OLYMPEX/RADEX SFs in Amiot et al. (2021), background WV was generally less than 20 kg m$^{-2}$; however, comparatively few values of WV < 20 kg m$^{-2}$ were observed during CAMP²Ex. Instead, a vast majority of CAMP²Ex observations were between 20 and 65 kg m$^{-2}$, with a slight local maximum around 30 kg m$^{-2}$ along with the aforementioned mode near 50 kg m$^{-2}$. Comparing individual flights (not shown), the minimum (maximum) WV median was 42.6 kg m$^{-2}$ (62.7 kg m$^{-2}$) in SF 17 (SF 10), as discussed further below.

Finally, AMPR’s median WS was 5.63 m s$^{-1}$ with a similar mode. This agrees with the 6.12 m s$^{-1}$ mean wind speed found around the central Pacific in West and Smith
FIG. 3.9. Histograms of precipitation-masked AMPR CLW (top), WV (middle), and WS (bottom) retrievals during SFs 05–19. Overall mean CLW, median WV, and median WS values calculated across these SFs are displayed in their respective panels.

(2021). In Fig. 3.9, WS followed a relatively uniform distribution about the median, with the exception of a cluster around 8.25–10 m s\(^{-1}\). Though not shown, flight-by-flight analyses indicated that median WS for SFs 06 and 10 were around 8.5–9 m s\(^{-1}\), likely due to synoptic conditions during both flights and the presence of a large cold pool sampled
throughout SF 10, which contributed to this secondary local maximum. Most AMPR pixels were associated with background WS of 3–11 m s\(^{-1}\). The minimum (maximum) WS median was 3.95 m s\(^{-1}\) (8.77 m s\(^{-1}\)) in SF 18 (SF 10).

That SF 18 (and SF 17; not shown) exhibited the lowest CLW and WS values may be due to the relatively small amount of convection observed by the P-3 during these two flights, combined with a physical connection between WS and CLW. Namely, increased wind speed would enhance surface heat and water vapor fluxes (e.g., Fairall \textit{et al}. 2003), generally leading to stronger and more frequent convection (all else being equal; e.g., Lucas \textit{et al}. 2000; Tompkins 2001; Nuijens and Stevens 2012). In addition, the lack of observed clouds would yield few opportunities for CLW and WS enhancements around regions of stronger convection (e.g., congestus). In contrast, the CLW and WS maxima during SFs 10 and 11 may have resulted from numerous deep-convection observations during these flights, allowing opportunities for CLW and WS enhancements at the fringes of AMPR’s precipitation masks, in addition to higher background winds enhancing surface heat and water vapor fluxes. The prevalence of convection during SF 10 and relative lack thereof during SF 17 indicate differences in background WV observed during these two flights, likely in direct connection with lower WS yielding lower surface water vapor flux. This idea is supported by an analysis (not shown) of the 15 individual median WV and WS values from SFs 05–19 (\textit{i.e.}, one value per flight), which indicated a moderately strong correlation coefficient of 0.75 between AMPR’s WV and WS retrievals.
3.4.2 AMPR CLW versus RSP CTH

This subsection details analyses of AMPR-derived CLW compared with RSP-derived CTH. Two versions were performed, one with AMPR’s precipitation masks applied and another without these masks. From Fig. 3.10, a common trend is present in both analyses, where AMPR’s CLW generally increased in a manner roughly proportional to \((\text{CTH})^2\) for CTH < 4 km AMSL. Given that LWC increases linearly with CTH (e.g., Miller et al. 2016), this \(\text{CLW} \propto (\text{CTH})^2\) relation follows expectations. However, once CTH passes 4 km AMSL, there is considerable clustering of data points around lower CLW. This is especially visible in the precipitation-masked scatterplot, but can be seen in both analyses. Given that AMPR’s CLW retrieval tends to fail in heavier precipitation (Amiot et al. 2021) and RSP is only sensitive to cloud liquid water, the data are largely from cloud water in both scatterplots. Thus, it is unexpected that data clustering would occur around lower CLW in association with high CTH.

One possible explanation for this behavior is the onset of accretion and/or freezing in the mixed-phase region. Once clouds grew deeper, increased accretion efficiency would result in transition of liquid water from being entirely cloud water to a mixture of cloud and rain water within the same column. Since AMPR CLW and RSP are not as sensitive to rain water as cloud water, these products would not display the rain water portion very well (if at all), but would continue to capture the cloud water portion during this transition. This would result in reduction of cloud liquid water path despite the increased CTH. Likewise, freezing of lofted cloud droplets would result in a transition of liquid water to ice water, which would reduce CLW (all else being equal). These ice processes become increasingly significant around 5 km AMSL, which is a
FIG. 3.10. Scatterplots of AMPR CLW (x axes) versus RSP CTH (y axes) across all coincident data points during SFs 05–19 with (left) and without (right) AMPR’s precipitation flags applied. Blue (green) data points represent those wherein the associated RSP-derived COT was ≤ 15 units (> 15 units). RSP data are reported in 100-m bins. A second-order best-fit line is shown in red for each plot, with the number of data points (n) and Pearson correlation coefficient (r) also displayed. Note that x-axis range differs between the plots for easier viewing of lower-CLW data points in the left plot.

Such a result is potentially important as it suggests that conversion of cloud water to rain and/or ice water became significant in CAMP²Ex’s maritime tropical environment once cloud-top height increased beyond approximately 4 km AMSL.

In addition to the accretion/mixed-phase hypothesis, there are other potential causes of the low-CLW/high-CTH data clustering. First, there were noted instances during CAMP²Ex where stratocumulus cloud layers impacted RSP CTH. In these cases, the mid-level cloud layer was reported as RSP CTH, but the layer may have been relatively shallow, yielding comparatively low AMPR CLW. To address this potential issue, the data in Fig. 3.10 were split into “low” and “high” COT groups using a threshold value of 15 units (Fu et al. 2022). While several of these low-CLW/high-CTH data points were associated with shallower clouds, many were associated with optically
thick clouds. Therefore, the unexpected CLW decrease with increasing CTH persisted in some thicker clouds. However, some effects of mismatched sampling between AMPR and RSP may be present. As discussed in section 3.3, it was challenging to correctly match data from two airborne instruments down to the fraction of a second, even when positioned on the same aircraft, and some slight temporal offsets (e.g., ~1 second) may exist. Since nadir data were considered from both instruments, it should be noted that AMPR and RSP operate with different footprint resolutions, which may have affected spatial matching of CLW-CTH data pairs. This is especially noteworthy when the P-3 passed slightly to the side of a congestus cloud, where AMPR may have (at least partly) missed the relatively thick cloud that RSP may have captured. As a result, further investigation into the low CLW values for CTH > 4 km AMSL is warranted.

### 3.4.3 Initial AMPR-AVAPS Comparisons

Examining AMPR vs AVAPS statistics throughout SFs 05–19, a couple of interesting trends were observed. These are briefly discussed herein and merit expansion during ongoing research, in addition to those that will be covered in chapter 4. Moderate correlations were observed between AVAPS-derived 0°C level height and AMPR’s CLW and WS retrievals (Fig. 3.11). In particular, a correlation coefficient of 0.49 (0.43) was found between AMPR’s mean CLW (median WS) and maximum AVAPS 0°C level from the corresponding flight; using mean 0°C (not shown) provided similar, but slightly weaker, correlations. This follows some physical expectations, as a deeper warm layer (i.e., temperatures > 0°C) would allow warm-rain processes to occur over a greater tropospheric depth, all else being equal. Since warm-rain processes are critical for
tropical convection \((e.g., \text{Mülenstädt et al.} 2015)\), stronger convection may occur within a deeper warm layer if all other environmental and storm-scale conditions were the same, which would yield higher CLW. Surface outflows from the resulting storm dissipation may yield local WS increases if hydrometeor mass loading and/or enhanced melting of precipitation ice hydrometeors (for storms with tops above the environmental 0°C level) were significant \((e.g., \text{Amiot et al.} 2019)\). However, a deeper warm humid layer would suppress evaporation and could hinder the formation of an intense outflow boundary \((e.g., \text{Grant and van den Heever} 2015)\).

Despite these trends, larger-scale environmental conditions would significantly influence the AMPR-AVAPS plots in Fig. 3.11, especially AVAPS and median WS since AMPR’s precipitation masks were used. Further, only 15 data points were used in these scatterplots, and additional analyses should be performed to examine these relationships with greater statistical significance.

3.5 Summary of Tropical Retrievals and Initial Science Applications

This chapter had two primary purposes: 1) demonstrate AMPR’s geophysical retrieval capabilities in the maritime tropics, including retrieval equation updates, and 2) present applications of these retrievals in addressing CAMP²Ex science questions. These retrievals were unique in their ability to be performed despite the presence of a radome, which was only the second time AMPR had operated with a radome and the first where a custom AMPR-specific radome was used. Applying retrievals previously derived for the midlatitudes in Amiot et al. (2021) indicated that the former water vapor (WV) method was suitable for the maritime tropics, while wind speed (WS) cross-track stripe artifacts
FIG. 3.11. Scatterplots of maximum AVAPS 0°C level height (x axes) compared with mean AMPR CLW (left plot) and median AMPR WS (right plot) during SFs 05–19.

and residual clear-air cloud liquid water (CLW) > 0 kg m⁻² were present throughout CAMP²Ex. To mitigate these, a new CLW equation was derived and corrections were developed for CLW and WS. The new CLW equation agreed very well with GDAS simulations, with RMSD of 1.94 x 10⁻² kg m⁻², mean retrieval error of 1.90 x 10⁻³ kg m⁻², and crosstalk errors with WV, WS, and SST of 1.37 x 10⁻², 3.60 x 10⁻³, and 4.79 x 10⁻⁴ kg m⁻², respectively. When applied to CAMP²Ex AMPR data, this updated equation significantly reduced residual CLW and mitigated clear-air cross-track variations. The corrected WS equation yielded a mean difference of 1.76 m s⁻¹ when compared against 144 dropsondes from SFs 05–19, which is less than the 2 m s⁻¹ target uncertainty. Similarly, AMPR’s CAMP²Ex WV retrievals differed from AVAPS-derived values by 8.27% on average, which is less than the 10% target uncertainty (including for the upcoming AOS mission).

Given significant CLW retrieval alterations since Amiot et al. (2021), multiple observational datasets were used for its validation. However, due to limitations in
correctly matching AMPR and dropsonde measurements for a single cloud, APR-3 and RSP data were employed. Comparing AMPR CLW with APR-3 Ka-band CLW yielded median absolute deviation, percentage deviation, and bias values of 0.432 kg m$^{-2}$, 85.7\%, and $-7.02 \times 10^{-2}$ kg m$^{-2}$, respectively. While percentage deviation and bias were relatively good, the comparatively high absolute deviation, about four times greater than the former CLW equation’s theoretical uncertainty, may have resulted from spatiotemporal matching issues between APR-3 and AMPR, $Z_H$ attenuation affecting vertical cloud profiling, and contamination from residual raindrops missed during precipitation masking. A lack of sensitivity to smaller cloud droplets for both Ku- and Ka-band data likely had a negative impact and reduced the retrieved CLW compared to higher frequencies. Along these lines, compared against RSP-derived CLW, AMPR’s CLW absolute deviations were significantly improved to a median of $8.08 \times 10^{-2}$ kg m$^{-2}$, which is less than the theoretical uncertainty of the original CLW method. The 865-nm data used in the RSP retrievals were more sensitive to cloud droplets than the APR-3 Ku- and Ka-band data, which likely contributed to the improved comparisons with AMPR CLW. Median AMPR CLW percentage deviation with RSP CLW was similar to the Ka-band analysis at 86.0\%, while median bias was slightly improved to $-3.28 \times 10^{-2}$ kg m$^{-2}$. The similarities between percentage deviations in the RSP and Ka-band comparisons may have resulted from greater sensitivity of Ka-band data to cloud droplets compared to Ku-band data. However, a relative lack of precipitation contamination in the RSP analyses, combined with the increased sensitivity to cloud water, indicates that the AMPR-RSP deviations were likely the most reliable indicators of AMPR’s CLW retrieval performances.
These retrievals were applied to \textsuperscript{2}CAMP science objectives via three initial analyses: 1) bulk AMPR statistics, 2) comparing AMPR CLW with RSP CTH, and 3) analyzing AMPR CLW and WS versus AVAPS-derived 0°C level height. AMPR’s mean CLW, median WV, and median WS outside of precipitation-flagged regions were 0.07 kg m\(^{-2}\), 49.7 kg m\(^{-2}\), and 5.63 m s\(^{-1}\), respectively, which were similar to expectations for the maritime tropics based on prior studies. Comparing AMPR CLW with RSP-derived CTH yielded an expected CLW \(\propto (\text{CTH})^2\) trend for CTH < 4 km AMSL. Once CTH increased past 4 km, CLW decreased considerably, which may indicate accretion and/or mixed-phase onset. AVAPS-derived environmental 0°C level height was moderately correlated with AMPR CLW and WS at 0.49 and 0.43, respectively.

These results help set the stage for future analyses. AMPR’s retrievals will be further compared with \textsuperscript{2}CAMP data from other P-3 (e.g., High Spectral Resolution Lidar 2) and/or Stratton Park Engineering Company Learjet-35 (e.g., cloud probes) instruments to examine aerosol influences on tropical cloud and storm processes, with the former covered in chapter 4. Incorporating modeling data to fill gaps in observations would benefit some analyses, such as the aforementioned aerosol-cloud-storm analysis. Additional CLW validation is desirable given limitations of some airborne remote-sensing analyses. Examining potential accretion/mixed-phase identification in AMPR-CLW/RSP-CTH more closely could provide useful verification of important processes in tropical convection. Developing AMPR retrievals for other geophysical products, such as surface rain rate, applicable to a wide range of climate regions is a possibility, and continuing to apply these techniques to past [e.g., Integrated Precipitation and Hydrology Experiment (IPHEx)] and future (e.g., AOS) field campaigns will be important.
Chapter 4. Expanded Environmental and Aerosol Analyses

This chapter greatly expands the science analyses of this dissertation by shifting the focus slightly away from AMPR’s retrievals and more toward addressing broader science questions that were investigated during CAMP²Ex by incorporating additional instruments that were deployed on the P-3 aircraft. The scientific focus of this chapter is on: 1) the influences of environmental conditions on remote-sensing parameters related to the intensity and/or frequency of convection, and 2) influences of aerosol concentration on these remote-sensing convective metrics when analyzed within groups that have been binned according to a specific environmental condition. The exact environmental conditions used in the latter analyses are varied through the use of different dropsonde-derived parameters, and the threshold values used to differentiate between low, medium, and high values of the given environmental parameter are varied in a sensitivity study. Bulk statistics are presented from each analysis, with additional discussions focusing on some of the strongest correlations discovered.

4.1 Purpose and Background

The purposes of this study are twofold: 1) expand the science applications of AMPR’s geophysical retrievals within the maritime tropical environment of CAMP²Ex, including a more in-depth implementation of these retrievals in addressing CAMP²Ex science questions; and 2) explore potential impacts of aerosol concentration on tropical
convection during CAMP$^2$Ex from a remote-sensing perspective. In particular, this research falls under the CAMP$^2$Ex science question of “To what extent are aerosol particles responsible for modulating warm and mixed-phase precipitation in tropical environments?”, while also having direct implications for impacts on deeper convection and cloud meteorology (ESPO 2020; Reid et al. 2023).

One of the greatest challenges in evaluating aerosol impacts on convection is to isolate the aerosols’ influences from other sources of convection modulation, such as atmospheric dynamics, thermodynamics, and cloud microphysical processes (e.g., Liu et al. 2016; Garbowski 2018). Since a given convective plume will be affected by synoptic-scale (i.e., > 2000 km), mesoscale α–γ (i.e., 2–2000 km), and sub-mesoscale-γ (i.e., < 2 km) dynamics (Orlanski 1975) and environmental conditions, it is especially important to understand, quantify, and constrain the environmental conditions associated with any convective element (herein “storm”) of interest. There are several environmental conditions with direct physical connections to convection that can be evaluated from remote-sensing and in situ observation platforms. Similar to chapter 3, AVAPS dropsondes were the primary dataset used to evaluate environmental conditions throughout CAMP$^2$Ex, given their direct in situ measurements of the parameters discussed below.

Past studies have explained and demonstrated a range of parameters that can be extracted from radiosonde data, the principles of which can be applied to dropsondes to the extent offered by the dropsonde’s launch altitude. One such parameter is vertical velocity ($w$) at the 700-hPa level, which can be used to diagnose vertical motion and associated support (detriment) for convection when positive (negative) values are
observed (Bony et al. 2004; Liu et al. 2016). Another widely used parameter for diagnosing potential updraft velocity in a given environment is Convective Available Potential Energy (CAPE), which is a measure of parcel buoyancy and can be defined mathematically as

\[
\text{CAPE} \left( J \text{ kg}^{-1} \right) = g \int_{z_{\text{LFC}}}^{z_{\text{EL}}} \frac{T_v - T_{v,0}}{T_{v,0}} \, dz,
\]

where \( g \) is gravitational acceleration, \( T_v \) and \( T_{v,0} \) are the virtual temperatures of a parcel and the environment, respectively, \( z \) is altitude, and \( z_{\text{LFC}} \) and \( z_{\text{EL}} \) are the altitudes of the level of free convection and equilibrium level, respectively (Markowski and Richardson 2010). While the shape of CAPE (Blanchard 1998) is not examined herein, it would be worth examining in future work given its importance to tropical convective intensity.

Further, the Lifting Condensation Level (LCL) altitude, which is the height at which a rising parcel of air becomes saturated and rises at the saturated, rather than dry, adiabatic lapse rate, is of interest to convection forecasting (Markowski and Richardson 2010). The LCL also serves as an indicator of cloud-base height (Markowski and Richardson 2010). While a surface-based parcel would be expected to reach saturation faster when the LCL altitude is lower (all else being equal), and thus experience warming from latent heat of condensation sooner than experienced under the same conditions with a higher LCL altitude, studies have demonstrated that a higher LCL altitude is often associated with wider updrafts and stronger vertical velocities owing to the entrainment of relatively dry air beneath the cloud base (Mulholland et al. 2021). Another metric related to forecasting the general frequency of convection under a given set of environmental conditions is the K-Index, which is expressed mathematically as

\[
\text{K-Index} \left( \degree \text{C} \right) = (T_{850} - T_{500}) + T_{d,850} - (T_{700} - T_{d,700}).
\]
where $T_{850}$, $T_{700}$, and $T_{500}$ are temperatures at the 850-, 700-, and 500-hPa levels, respectively, and $T_{d,850}$ and $T_{d,700}$ are dew point temperatures at the 850- and 700-hPa levels, respectively (George 1960). From Eq. 21, the K-Index takes into account: 1) low-to-mid-level temperature lapse rate, 2) low-level dew point temperature ($T_d$), and 3) mid-level $T_d$ depression, with the former two (latter one) being directly (inversely) related to convective potential. However, the K-Index is meant to serve as a general indicator of convective potential, rather than an indication of convective intensity (George 1960).

As noted previously, temperature lapse rates in the lower and middle atmosphere have direct implications for convective potential given their indication of instability over a given atmospheric layer. In particular, temperature lapse rate in the 700–500-hPa layer has been shown to serve as an excellent indicator of convective potential (e.g., Sherburn and Parker 2014). Others have noted the utility of the 850–700-hPa lapse rate in forecasting convective potential due to its association with parcel vertical acceleration in the lower atmosphere (e.g., Wang et al. 2015 and Eq. 21). Lastly, low-level $T_d$ has been shown to be important to convective intensity due to entrainment of relatively high-water-vapor air into the base of an updraft (e.g., Lucas et al. 2000).

To evaluate the presence and intensity of convection, various remote-sensing observations have been used in past works. For the purposes of this study, microwave remote-sensing signatures from radar and radiometer will be the primary focus. When examining radar observations of convection, 30-dBZ $Z_H$ has often been used to identify precipitation regions (e.g., Straka et al. 2000) and delineate between different “storms” or “cells” (e.g., Johnson et al. 2008; Hastings and Richardson 2016; Amiot et al. 2019). Peak height of the 30-dBZ contour in a given storm is also directly related to updraft
magnitude and storm intensity (e.g., Straka et al. 2000; Amiot et al. 2019), which will be examined in future work for this study. As precipitation-sized hydrometeors form and begin to grow within a given storm, $Z_H$ rapidly increases due to the weighting of hydrometeor diameter to the 6th power associated with Rayleigh scattering (Rinehart 2010). However, once a hydrometeor grows such that its diameter is larger than one-tenth the radar wavelength, non-Rayleigh resonance effects will begin (Rinehart 2010); this is especially important to note at finer wavelengths, such as the 2.2- and 0.84-cm wavelengths associated with APR-3’s Ku and Ka band, respectively (Durden et al. 2020).

As discussed in chapter 2, microwave radiometer measurements will generally yield higher $T_b$ values at increasingly lower frequencies as precipitation hydrometeors continue to grow (in the absence of ice formation aloft; e.g., Spencer et al. 1994). This makes it possible to retrieve integrated cloud and precipitation properties using combinations of $T_b$, such as demonstrated by Amiot et al. (2021) and in chapter 2. For AMPR specifically, CLW retrievals would be expected to fail as precipitation increases in size and/or concentration due to the structure of the multi-linear regression equation (i.e., Eqs. 6 and 19), as shown in chapter 2. Thus, as a cloud grows vertically, CLW is expected to increase until the retrieval fails in moderate-to-heavy precipitation (Amiot et al. 2021). Despite this failure, the CLW increase around the precipitation core could yield useful information about the associated convective intensity. For example, the presence of precipitation is often associated with cumulus clouds at least 1.5–2 km tall (Smalley and Rapp 2020), and CLW $>$ 1 kg m$^{-2}$ may further indicate the formation of precipitation within these clouds (e.g., Jiang and Zipser 2006).
The influence of aerosols on convective storms has been a topic of significant research over the past several decades. Increased aerosol concentration is generally associated with an increased number of cloud condensation nuclei (CCN), with the efficiency of an aerosol in serving as a CCN depending on its composition; however, composition is mainly significant if it is < 10% soluble, while the aerosol size distribution exerts a stronger influence over the cloud particle size distribution (Junge and McLaren 1971). In shallow clouds, the first indirect effect of aerosols is to increase the number concentration of cloud droplets, which will increase the total atmospheric albedo (all else being equal; Twomey 1977). The second indirect effect of aerosols in shallow clouds is to favor a decrease in precipitation formation and increase in a given cloud’s lifetime (Albrecht 1989), which results from reduced cloud droplet sizes due to increased competition for the finite amount of available water vapor (e.g., Rosenfeld and Lensky 1998; Sherwood 2002). However, the precipitation-sized hydrometeors that do form under higher aerosol concentrations are generally larger, owing to ample cloud droplets available for collection (e.g., Stroud et al. 2007; Altaratz et al. 2008; Saleeby et al. 2010).

Warm-phase invigoration of tropical convection due to aerosol influences has been explored and demonstrated in many past studies. Sheffield et al. (2015) demonstrated how enhanced aerosol concentrations can lead to increased cloud water content and more vigorous updrafts, which largely result from enhanced water vapor condensation onto the greater number of CCN in the warm-phase cloud region and a corresponding increase in latent heat released compared to more-pristine conditions. Likewise, Marinescu et al. (2021) noted a 5–15% increase in mean updraft velocity around 4–7 km AGL for cases where CCN concentrations were relatively high. Smaller
cloud droplets associated with higher aerosol concentrations may also enhance updraft/convective intensity via increased freezing above the environmental 0°C level and resulting latent heat exchanges (e.g., van den Heever and Cotton 2007; Rosenfeld et al. 2008). However, the increase in convective intensity has been shown to be primarily driven by condensational heating in the lower levels of the atmosphere, rather than freezing above the environmental 0°C level (Igel and van den Heever 2021; Cotton and Walko 2021), further indicating the importance of evaluating aerosol concentrations within/around the warm-phase region of a given cloud.

Despite these enhancements from higher aerosol concentrations, entrainment of relatively dry environmental air into a cloud, especially near cloud top, may cause rapid evaporation of the smaller cloud droplets, leading to a decrease in overall cloud/storm structure (e.g., Liu et al. 2016). This indicates that a “Goldilocks” zone of middle-ground aerosol concentration may be the favored condition for enhanced convection (e.g., Sokolowsky et al. 2022). Additional studies have supported the notion of increased aerosol concentration favoring convection (e.g., van den Heever et al. 2006), while others have discussed the considerable difficulty in separating aerosol influences from atmospheric dynamics (e.g., Garbowski 2018), which highlights several uncertainties surrounding the influences of aerosol concentration on convective intensity.

One remote-sensing instrument that has been employed in aerosol analyses is lidar, an example of which is the airborne High Spectral Resolution Lidar 2 (HSRL2) that deployed on the NASA P-3 aircraft during CAMP²Ex (Hostetler 2020). HSRL2 measures aerosol backscatter and depolarization ratio at three wavelengths centered at 355, 532, and 1064 nm, with aerosol extinction and aerosol optical thickness (AOT) data.
also available at 355 and 532 nm (Hostetler 2020). Lenhardt et al. (2022) demonstrated how HSRL2’s extinction and backscatter coefficients have strong direct correlations with CCN concentrations, with a slightly stronger correlation observed between CCN concentration and the 532-nm parameters despite the finer resolution of the 355-nm channel. Additional studies (e.g., Liu et al. 2016) have noted a direct correlation between lidar-based AOT and CCN concentration. As a result, extinction, backscatter, and AOT may all be considered when examining aerosol concentration. However, the height/location of a given aerosol layer is important to consider as well when evaluating the impacts of radiation absorption and local warming (e.g., Chand et al. 2009; Redemann et al. 2021). Information about aerosol altitude can be obtained using extinction and backscatter data, but the vertical integration involved in calculating AOT removes the ability to gather this information solely using AOT values.

The primary difference between the two HSRL2 channels, as noted previously, is the finer resolution of the 355-nm channel, increasing sensitivity to smaller aerosols (e.g., Burton et al. 2018), while the primary differences between extinction, backscatter, and AOT are largely tied to the methods in which they are retrieved or derived. For example, Lenhardt et al. (2022) noted that the correlation between HSRL2 backscatter and CCN concentration was slightly higher than the relation between extinction and CCN concentration, which they suggested may have been due to raw backscatter measurements offering finer-resolution data compared to the coarser resolution of the extinction coefficient calculations via Burton et al. (2016). In addition, Lenhardt et al. (2022) noted that AOT may be influenced by aerosol water absorption in a given scene, which would increase AOT but not necessarily CCN concentration, thus affecting interpretations.
Based on these studies, the specific science questions to be addressed herein are as follows:

1) How do radiometer- and radar-based metrics of storm intensity and frequency vary with different dropsonde-measured environmental indicators of convective intensity and/or potential throughout CAMP²Ex?

2) When binned into similar environmental groups, how do the same radar- and radiometer-based metrics of storm intensity and frequency vary with lidar-based observations of aerosol concentration?

The results of these analyses are important as they provide insight into science questions for a major NASA field campaign, have relevance to upcoming NASA missions (e.g., AOS), and contribute knowledge to long-standing questions of aerosol influences on convection. Based on prior studies, it is hypothesized that the radar- and radiometer-based metrics of storm intensity and/or frequency would all increase under greater 700-hPa w, CAPE, K-Index, lapse rates, and low-level T_d. The expectations for LCL altitude were more uncertain, given the greater low-level water vapor content associated with low LCL altitude but the tendency for higher LCL altitude to favor stronger updrafts due to cloud-base entrainment (Mulholland et al. 2021). Based on the latter study, it is hypothesized that higher LCL altitude may correlate directly with storm intensity and/or frequency. That is, a positive correlation would be expected between the microwave remote-sensing signatures and the environmental parameters due to their direct associations with convective intensity and/or frequency. Further, it is hypothesized that radiometer-retrieved CLW, peak radar Z_H, and the abundance of Z_H observations > 30 dBZ within a given scene will all increase under higher aerosol concentrations within
a given environmental group. These hypotheses are based on the expectation that increased aerosol concentration would favor the development of smaller and more numerous cloud droplets, which would enhance convection and CLW, while the presence of fewer but larger raindrops would yield a higher peak $Z_H$ and overall presence of $Z_H > 30$ dBZ. While it is acknowledged that there are inherent difficulties, limitations, and uncertainties associated with separating aerosol and environmental influences on convection (e.g., Garbowski 2018), potential trends found in the CAMP$^2$Ex dataset could provide useful information to support future work. Section 4.2 covers the data and methods used in this study, with section 4.3 presenting results from the environmental analyses, section 4.4 highlighting the environmental stratification and aerosol analyses, and section 4.5 presenting a summary and future work.

4.2 Overview of Data and Analysis Methods

Similar to chapter 3, all AMPR, APR-3, and AVAPS data used in this analysis were gathered from the CAMP$^2$Ex data repository (Aknan and Chen 2020). The HSRL2 data were also obtained from Aknan and Chen (2020), though only the 355- and 532-nm channels were used due to some products (e.g., AOT) being unavailable at 1064 nm. Due to the direct correlations between CCN concentration and lidar extinction, backscatter, and AOT, all three parameters were analyzed from both HSRL2 channels, though 532-nm backscatter was of particular interest based on discussions in Lenhardt et al. (2022). The same QC processes outlined in section 3.2 for the AMPR, APR-3, and AVAPS data were applied for this study, including application of AMPR’s data quality flags and removal of the same 10 APR-3 files and 10 AVAPS dropsondes. The HSRL2 data were
screened for clouds prior to their acquisition (Hostetler 2020) to avoid potential contamination of the aerosol analyses (e.g., Liu et al. 2016).

Environmental conditions throughout CAMP$^2$Ex were examined as a starting point for this study. This decision was made to: 1) evaluate environmental conditions across all SFs on their own, and 2) begin developing environmental constraints for the eventual aerosol analyses. As such, nine environmental parameters with known physical connections to convective intensity were selected. These nine parameters were just some of the many parameters that have demonstrated connections with convective intensity and/or frequency, and were selected based on their ability to be fully captured by a statistically significant number of CAMP$^2$Ex dropsondes. Future work should consider additional environmental conditions. The nine selected environmental parameters were:

1) Vertical velocity ($w$) at the 700-hPa level;
2) Modified CAPE;
3) LCL altitude;
4) K-Index;
5) Temperature lapse rate (LR) between the 850- and 700-hPa levels;
6) Temperature LR between the 850- and 500-hPa levels;
7) Temperature LR between the 700- and 500-hPa levels;
8) Mean $T_d$ below the 925-hPa level;
9) Mean $T_d$ below 1 km AGL.

Vertical ascent is a parameter included within the AVAPS dataset (Vömel et al. 2020) and is based on the fall-speed characteristics of the dropsonde (Freeman et al. 2020). The ascent value from the pressure array element nearest 700 hPa was used as the
700-hPa w. Since CAPE is related to integrated buoyancy between the LFC and EL (Eq. 20), an issue arises with computing CAPE from AVAPS during CAMP²Ex; since the P-3 did not fly above the EL during any of the SFs, the dropsondes were unable to capture the full vertical profile of buoyancy associated with traditional CAPE. As such, the term “modified CAPE” is used herein, and is defined mathematically as

$$\text{CAPE} \left( \text{J kg}^{-1} \right) = g \int_{z_{LFC}}^{z_{P3}} \frac{T_v - T_{v,0}}{T_{v,0}} \, dz,$$

(22)

where $z_{P3}$ is the P-3 altitude and all other terms are the same as in Eq. 20. With this definition, the modified CAPE would typically be less than the true CAPE value within the same environment, which limits the evaluation of parcel buoyancy. However, since the dropsondes were often launched when the P-3 altitude was $> 4$ km (Vömel et al. 2020), the instability indicated by modified CAPE can be compared and contrasted across the environments. Despite this, the P-3 altitude would have a direct effect on modified CAPE calculated via Eq. 22, with lower altitude (e.g., around 4 km AGL) biased toward lower modified CAPE by virtue of the dropsonde capturing a lesser vertical extent of the parcel buoyancy. All CAPE values were calculated using the “mixed_layer_cape_cin” function within Python’s MetPy package (May et al. 2022).

The LCL altitude in each dropsonde was calculated using the “calc.lcl” function within Python’s MetPy package (May et al. 2022). In contrast, the K-Index was calculated semi-manually by identifying the pressure array elements nearest the 850-, 700-, and 500-hPa levels, extracting the associated $T$ and/or $T_d$ values from these elements, and utilizing Eq. 21. In a similar manner, the temperature and altitude values from array elements nearest the 850-, 700-, and 500-hPa levels were used to calculate the 850–700-, 850–500-, and 700–500-hPa temperature lapse rates via the relation
\[
LR \left( ^\circ C \text{ km}^{-1} \right) = - \frac{(T_{\text{upper}} - T_{\text{lower}})}{(z_{\text{upper}} - z_{\text{lower}})},
\]

where LR is lapse rate, \( T_{\text{upper}} \) and \( T_{\text{lower}} \) are temperatures at the higher and lower altitudes, respectively, and \( z_{\text{upper}} \) and \( z_{\text{lower}} \) are the higher and lower altitudes, respectively. Lastly, mean low-level \( T_d \) values were calculated by finding the array elements where: 1) pressure was > 925 hPa, or 2) altitude was < 1 km AGL, and calculating the mean of all \( T_d \) values from the associated array elements.

Once the above parameters were calculated from each dropsonde throughout CAMP\(^2\) Ex SFs 05–19, they were matched spatiotemporally with AMPR and APR-3 variables with physical connections to convective intensity and/or frequency. To begin this process, the APR-3 filenames were examined and the start and end times of each APR-3 file were extracted. The decision was made to focus on APR-3 times as a single APR-3 scan takes less than 2 seconds to complete, making it the highest-resolution temporal dataset of the instruments utilized in this study. The launch time of each dropsonde was compared with these start and end times, and the APR-3 file during which the given dropsonde was launched was identified; this was repeated for all 144 dropsondes from SFs 05–19. For each of these 144 APR-3 files, the associated start and end times were used to define the time of a single “scene” for the analyses discussed below. Because of this, the total duration of each “scene” in this analysis varied, but was typically 2–12 minutes (Fig. 4.1). For consistency in the total time covered by each analysis, the AMPR and HSRL2 scans nearest the start and end time of each APR-3 file were noted, and all AMPR, APR-3, and HSRL2 data were examined over the same approximate time period within each scene.
Three different remote-sensing parameters related to convective intensity and/or frequency were preliminarily calculated in each scene: 1) maximum AMPR CLW, 2) maximum APR-3 Ku-band composite $Z_H$, and 3) number of APR-3 Ku-band composite $Z_H$ pixels $> 30$ dBZ. Maximum values were used for the former two parameters due to their direct association with peak convective intensity (i.e., enhanced warm-cloud depth and raindrop size, respectively). To calculate composite $Z_H$, the same data QC described in section 3.2 was firstly applied to all APR-3 data. However, unlike section 3.2, the QC process was applied to all 25 APR-3 scan angles in each scene, rather than just the nadir scan. Within each column of APR-3 data, the maximum $Z_H$ between the P-3 altitude and the surface, as flagged by the first scan in the data file, was used as the composite $Z_H$. This process was repeated for all APR-3 columns in each QC’d file across SFs 05–19. During visual inspection of the resulting data, the presence of occasional residual near-surface range-/sidelobe effects at off-nadir scan angles was noted, which often manifested as very high composite $Z_H$ (i.e., $> 70$ dBZ). As a basic restriction, all composite $Z_H$ pixels $> 70$ dBZ were excluded from the analyses herein, but some erroneous pixels may still reside in the final dataset (e.g., isolated cases where some noisy pixels and/or near-
surface range-/sidelobe effects with $Z_H < 70$ dBZ remained). Once all composite $Z_H$ values were calculated, the maximum composite Ku-band $Z_H$ within each scene was noted, as were the number of Ku-band composite $Z_H$ pixels $> 30$ dBZ. In addition, the maximum AMPR CLW within each scene was recorded.

As a preliminary examination, which will be presented in section 4.3 below, these three convective parameters were compared with the nine dropsonde parameters within each of the 144 scenes. The results of this analysis were examined using Pearson and Spearman correlation coefficients to identify potential relationships between the two datasets, with the strongest Pearson correlation coefficients examined in more detail using scatterplots. It should be noted that the exact number of data points in each scatterplot varied due to variations in missing data. For example, since the 850–500-hPa lapse rate, 700–500-hPa lapse rate, and K-Index all require the presence of 500-hPa data, any dropsonde launched when the P-3 was below the 500-hPa level was excluded from these calculations. In addition, several scenes contained no unmasked APR-3 and/or AMPR data, resulting in their exclusion from the comparisons.

To begin isolating potential aerosol influences on tropical convection, two steps were employed: 1) bin the environmental scenes into different groups based on a particular AVAPS parameter and magnitude, and 2) incorporate HSRL2 data into this analysis. The same nine AVAPS parameters listed above were employed. To stratify each environment, a single AVAPS parameter was separated into “low,” “medium,” and “high” values, and each scene was grouped into one of these categories based on the associated dropsonde’s values, as discussed further below. Once the dropsondes were split into their respective groups, the maximum AMPR CLW, maximum APR-3 Ku-band
composite $Z_{H}$, and number of APR-3 Ku-band composite $Z_{H}$ pixels > 30 dBZ were compared to the dropsonde parameters using Pearson and Spearman correlation coefficients. In addition, APR-3’s Ka-band data were incorporated into this analysis, with all data QC and composite $Z_{H}$ calculations discussed previously applied. As a result, maximum APR-3 Ka-band composite $Z_{H}$, and number of APR-3 Ka-band composite $Z_{H}$ pixels > 30 dBZ were also compared with the dropsonde data, yielding a total of five “convective parameters/metrics” for this analysis.

Within each environmental bin, the five convective parameters were compared against maximum values of the six HSRL2 parameters (i.e., AOT, extinction, and backscatter, each at 355 and 532 nm) within each scene. The Pearson and Spearman correlation coefficients from these comparisons were the final values reported, as were the number of data points used in each comparison. In addition, it was noted if the correlation was statistically significant based on whether the associated p-value was < 0.01 (e.g., Wilks 2011).

Lastly, the exact values used to stratify each environmental condition were varied in a sensitivity test consisting of four different sets of thresholds for each parameter. The threshold values from each test are listed in Table 4.1. The methods used to stratify the environmental parameters in Tests #1–4 were, respectively, as follows:

1) Create campaign-wide histograms of the AVAPS parameter and visually identify approximate values that roughly split the dataset into three equal-sized groups;

2) Use Python’s “numpy.percentile” function (Harris et al. 2020) to objectively select thresholds that split each parameter’s dataset into three equal-sized groups;
3) Manually select thresholds that fall between the low-medium and medium-high thresholds previously identified in Tests #1 and #2;

4) Use Python’s “numpy.percentile” function to objectively select thresholds that split each parameter’s dataset into three groups where the “low” and “high” categories each contain 25% of the data and the “medium” category contains 50% of the data (i.e., a “medium” dataset for each parameter that was approximately twice as large as the “low” and “high” datasets).

4.3 Initial Campaign-wide Environmental Analyses

This section presents the results of comparing the nine AVAPS parameters against maximum AMPR CLW, maximum APR-3 Ku-band composite $Z_H$, and number of APR-3 Ku-band composite $Z_H$ pixels $> 30$ dBZ for the 144 scenes across CAMP$^2$Ex SFs 05–19. No APR-3 Ku- or Ka-band data were left from SF 05 after data QC, resulting in the case being excluded from the final statistics. Broad results are presented in the form of correlation tables, with scatterplots used to examine the strongest correlations in greater detail.

4.3.1 AMPR Results

The full results of comparing maximum AMPR CLW with the nine dropsonde parameters across CAMP$^2$Ex can be found in Tables 4.2 and 4.3. From Table 4.2, it can be seen that there was relatively weak to no correlation between most of the AVAPS parameters and maximum AMPR CLW within the same scene when analyzed from a campaign-wide perspective. This was unexpected, as trends related to convective
TABLE 4.1. List of the four sensitivity tests that were performed to stratify the nine AVAPS parameters into “Low,” “Medium,” and “High” bins. The listed values in each bracket represent the inclusive range of the “Medium” bin for the respective parameter and test; that is, values less (greater) than the lower (upper) limit were classified into the “Low” (“High”) bin. “np” is an abbreviation for NumPy (Harris et al. 2020).

<table>
<thead>
<tr>
<th>AVAPS Parameters</th>
<th>Sensitivity Tests and How Stratification Values were Determined</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Test 1: Visual Histogram Analysis</td>
</tr>
<tr>
<td>700-500-hPa LR</td>
<td>[5.5, 6.0] °C/km</td>
</tr>
<tr>
<td>850-500-hPa LR</td>
<td>[5.0, 5.5] °C/km</td>
</tr>
<tr>
<td>LCL Alt</td>
<td>[400, 550] m</td>
</tr>
<tr>
<td>700-hPa w</td>
<td>[-0.25, 0.25] m/s</td>
</tr>
</tbody>
</table>

Intensity were anticipated between the radiometer and dropsonde parameters. However, there are several factors that may have contributed to these results. First, as noted previously, AMPR’s peak CLW falls just outside of precipitation regions, since Eq. 19 tends to fail in regions of moderate-to-strong rainfall, which would be expected in the most intense convective storms. While it was hypothesized that AMPR CLW would increase to a higher value immediately adjacent to the “failure point” in a stronger storm compared to a weaker storm, this did not seem to take place in a manner sufficient to influence the correlations in Table 4.2.

Additionally, while the environments sampled across CAMP²Ex were very heterogeneous (e.g., Reid et al. 2023) a few of the dropsonde parameters in Table 4.2 varied by relatively small amounts or magnitudes across the campaign (e.g., mean low-level T_d varied by about 4°C across the dropsondes examined; not shown). This could have caused some of the correlations in Table 4.2 to be restricted compared to others (e.g., a much wider range of CAPE values were observed). In addition, convection was present throughout many of the SFs and dropsonde launches, which would have modified
TABLE 4.2. Pearson correlation coefficient values between the nine AVAPS dropsonde parameters (left column) and the AMPR and APR-3 convective parameters (top row). Parenthesized values indicate the number of dropsondes/scenes used in the comparisons, and an asterisk indicates that the associated Pearson correlation coefficient’s p-value was < 0.01.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>AMPR Max CLW</th>
<th>APR-3 Ku-band Max ZH</th>
<th>APR-3 Ku-band # Pixels &gt; 30 dBZ</th>
<th>Color Legend</th>
</tr>
</thead>
<tbody>
<tr>
<td>Td 1 km</td>
<td>0.14 (123)</td>
<td>-0.06 (94)</td>
<td>0.05 (104)</td>
<td>0.80–1.00</td>
</tr>
<tr>
<td>Td 925 hPa</td>
<td>0.05 (123)</td>
<td>-0.06 (94)</td>
<td>0.02 (104)</td>
<td>0.60–0.79</td>
</tr>
<tr>
<td>700-500 LR</td>
<td>0.15 (44)</td>
<td>0.21 (34)</td>
<td>-0.04 (39)</td>
<td>0.40–0.59</td>
</tr>
<tr>
<td>850-500 LR</td>
<td>-0.11 (44)</td>
<td>-0.08 (34)</td>
<td>-0.13 (39)</td>
<td>0.20–0.39</td>
</tr>
<tr>
<td>850-700 LR</td>
<td>-0.44 (121)*</td>
<td>-0.21 (93)</td>
<td>0.05 (103)</td>
<td>-0.19–0.19</td>
</tr>
<tr>
<td>K-Index</td>
<td>-0.08 (44)</td>
<td>-0.22 (34)</td>
<td>-0.12 (39)</td>
<td>-0.20–0.39</td>
</tr>
<tr>
<td>LCL Alt</td>
<td>-0.16 (123)</td>
<td>0.07 (94)</td>
<td>-0.01 (104)</td>
<td>-0.40–0.59</td>
</tr>
<tr>
<td>CAPE</td>
<td>0.00 (123)</td>
<td>-0.02 (94)</td>
<td>0.15 (104)</td>
<td>-0.60–0.79</td>
</tr>
<tr>
<td>700-hPa w</td>
<td>-0.13 (121)</td>
<td>0.09 (93)</td>
<td>-0.07 (103)</td>
<td>-0.80–1.00</td>
</tr>
</tbody>
</table>

the environments from their original (i.e., “pre-storm”) state and might have contributed to the unexpected correlations. Finally, an overall limitation of this analysis is that the convective storms analyzed were limited to those that the P-3 flew over or into. While cumulus-type clouds were of great interest to many SFs, other SFs had other science foci, such as radiation and aerosol composition. As a result, many of the stronger storms were not sampled by the P-3 in several environments. Along these lines, the P-3 avoided the strongest storms in each flight (e.g., cumulonimbus, if any were present), both for safety reasons and because these types of storms were not part of the CAMP$^2$Ex science goals. Thus, it is possible that stronger storms were present around a given flight path but were not captured by the P-3 instruments. Further, in cases where these deep convective storms were nearby but outside the P-3 flight path, associated subsidence may have been measured by the dropsondes and contributed to some of the low correlations in Table 4.2.

Despite these limitations, a few interesting trends were present in the environmental analysis. In the AMPR comparisons, a moderate Pearson correlation coefficient of -0.44 was observed between the 850–700-hPa LR and peak CLW, which had statistical significance. However, the correlation between these two parameters was
expected to be positive, rather than negative, and a similar trend is present in the Spearman correlation coefficient in Table 4.3. Therefore, a more in-depth examination of the individual data points was warranted. From the scatterplot in Fig. 4.2, it can be seen that there was a relatively narrow range of 850–700-hPa lapse rates between 3 and 6 °C km\(^{-1}\) observed in the dropsonde scenes, indicating relatively stable to conditionally unstable environments. That is, the low-level lapse rates did not appear to be the most favorable for development of deep convection; however, as noted above, it is possible that deeper convection was present and not fully captured by the P-3. Further, the five data points farthest right in the plot space likely influenced the magnitude of moderate correlation coefficient, though the observed correlation was of statistical significance. Due to this statistical significance, the unexpected negative correlation cannot be rejected, and further investigation is needed.

4.3.2 APR-3 Results

The results of comparing APR-3’s Ku-band peak composite \(Z_H\) and number of Ku-band composite \(Z_H\) pixels > 30 dBZ with AVAPS in each scene can also be found in Tables 4.2 and 4.3. From Table 4.2, three AVAPS parameters passed the “moderately weak” Pearson correlation coefficient threshold of ±0.20 in the APR-3 maximum \(Z_H\) analysis: K-Index, 850–700-hPa LR, and 700–500-hPa LR, which was more than the single correlation magnitude > 0.20 in the AMPR CLW analysis. However, the correlation magnitudes were lower for most parameters in the APR-3 peak \(Z_H\) analysis, with the highest correlation magnitude being 0.22. These results follow a similar trend as in the AMPR CLW analysis, with little correlation between the radar and dropsonde
TABLE 4.3. As in Table 4.2, but for Spearman correlation coefficients and p-values.

<table>
<thead>
<tr>
<th>Parameters</th>
<th>AMPR Max CLW</th>
<th>APR-3 Ku-band Max ZH</th>
<th>APR-3 Ku-band # Pixels &gt; 30 dBZ</th>
<th>Color Legend</th>
</tr>
</thead>
<tbody>
<tr>
<td>Td 1 km</td>
<td>0.10 (123)</td>
<td>-0.00 (94)</td>
<td>0.02 (104)</td>
<td>0.80–1.00</td>
</tr>
<tr>
<td>Td 925 hPa</td>
<td>-0.01 (123)</td>
<td>0.00 (94)</td>
<td>0.01 (104)</td>
<td>0.60–0.79</td>
</tr>
<tr>
<td>700-500 LR</td>
<td>-0.04 (44)</td>
<td>0.17 (34)</td>
<td>-0.03 (39)</td>
<td>0.40–0.59</td>
</tr>
<tr>
<td>850-500 LR</td>
<td>-0.16 (44)</td>
<td>-0.11 (34)</td>
<td>-0.26 (39)</td>
<td>0.20–0.39</td>
</tr>
<tr>
<td>850-700 LR</td>
<td>-0.43 (121)*</td>
<td>-0.15 (93)</td>
<td>-0.01 (103)</td>
<td>-0.19–0.19</td>
</tr>
<tr>
<td>K-Index</td>
<td>0.00 (44)</td>
<td>-0.22 (34)</td>
<td>-0.22 (103)</td>
<td>-0.20–0.39</td>
</tr>
<tr>
<td>LCL Alt</td>
<td>-0.16 (123)</td>
<td>0.07 (94)</td>
<td>-0.08 (104)</td>
<td>-0.40–0.59</td>
</tr>
<tr>
<td>CAPE</td>
<td>-0.01 (123)</td>
<td>-0.04 (94)</td>
<td>0.04 (104)</td>
<td>-0.60–0.79</td>
</tr>
<tr>
<td>700-hPa w</td>
<td>0.04 (121)</td>
<td>0.15 (93)</td>
<td>-0.02 (103)</td>
<td>-0.80–1.00</td>
</tr>
</tbody>
</table>

parameters. Because these trends were present in both the AMPR and APR-3 analyses, they seem most likely to result from a limitation in the dataset and/or analysis methods, mainly the aforementioned lack of sampling the strongest convection on a given day and modification of the environmental conditions by the presence of nearby storms. However, the Pearson correlation coefficient for the 850–700-hPa LR had a relatively low p-value (i.e., > 0.01 but < 0.05; not shown) and a relatively large sample size of 93, despite its weak correlation magnitude. A more in-depth analysis of this parameter is shown in Fig. 4.3, where it can be seen that the unexpected negative correlation, similar to the AMPR CLW analysis, may have been influenced by a few data points near the left side of the plot. Therefore, the correlation between these parameters would likely be weaker if these data points were removed. Based on these trends, there did not seem to be a strong correlation between APR-3 Ku-band peak composite $Z_H$ and any of the dropsonde parameters.

Lastly, correlations between the nine AVAPS parameters and the number of APR-3 Ku-band composite $Z_H$ pixels > 30 dBZ within the same scene can be found in Tables 4.2 and 4.3. From Table 4.2, all Pearson correlation coefficients were extremely weak for these comparisons, with the highest magnitude being 0.15 for CAPE, and none

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FIG. 4.2. Scatterplot of maximum AMPR CLW versus AVAPS-measured 850–700-hPa lapse rate across CAMP\textsuperscript{2}Ex SFs 05–19. The Pearson correlation coefficient (r) is indicated, and the solid blue line represents a single-order polynomial best-fit line to the data.

of which were statistically significant. In Table 4.3, K-Index and 850–500-hPa LRs had weak Spearman correlation coefficients with number of $Z_H$ pixels > 30 dBZ, but none were statistically significant based on their p-value. This trend was interesting, as this particular APR-3 parameter was based on general observed convection, rather than a peak $Z_H$ value as in the previous analysis. Thus, it was initially hypothesized that this
parameter would have stronger correlations with the dropsonde parameters, especially those that are generally indicative of convective potential (e.g., K-Index). If convection were evenly distributed over an area of the CAMP²Ex domain, it would also be more likely for some precipitation to be observed, even if the storms were not the most intense within the domain. However, this was not the case when the results were visualized.
To better evaluate a trend in these data, Fig. 4.4 was examined due to its association with the highest Spearman correlation coefficient. From Fig. 4.4, it can be seen that the number of observed pixels > 30 dBZ was most often < 800, with only seven scenes across the field campaign coinciding with more than 800 composite Z̴H pixels > 30 dBZ. Thus, variation in the environmental parameters (i.e., spread of data points along the y-axis in Fig. 4.4) would yield a low correlation with a dataset that was generally limited along the x-axis with a few outlier data points. This analysis may have also been affected by variations in the “scene” times associated with the APR-3 file start and end times, as a longer scene time would allow more opportunities for Z̴H pixels > 30 dBZ to be observed for a given dropsonde. That is, a few longer scene times may have caused the appearance of the few outliers in Fig. 4.4, and future work might want to reevaluate this comparison using a set length of scene time across the campaign.

4.4 Environmental Stratification and Aerosol Influences on Convection

This section presents the results of comparing the AMPR and APR-3 convective parameters with HSRL2 data within environmental bins as constrained by different threshold values within nine AVAPS parameters. In addition to AMPR and Ku-band APR-3 data, Ka-band APR-3 data are included in these comparisons. In each subsection, similar to section 4.3, a complete description of the correlations is provided in the form of a correlation table, with a more in-depth discussion and analysis performed for some of the strongest and potentially most impactful correlations. The results from Test #2 in Table 4.1 are the primary focus in these analyses, given that the AVAPS bins were split into roughly equal-sized groups (with some comparisons ultimately excluded due to
FIG. 4.4. As in Fig. 4.2, but for the comparison of number of APR-3 Ku-band composite $Z_H$ pixels $> 30$ dBZ and AVAPS-derived 850–500-hPa lapse rate.

missing data, etc.) using a more objective method (i.e., via the “numpy.percentile” function, rather than manual threshold selections) in Test #2. A description of the AVAPS stratification sensitivity-test results is provided for each parameter, and all associated correlation tables from these sensitivity tests can be found in Appendix B.
4.4.1 AMPR Results

To begin, each of AMPR’s CLW comparisons with the six HSRL2 parameters within the environments stratified by each AVAPS parameter and magnitude in Test #2 can be summarized in Fig. 4.5. From Fig. 4.5, it can be seen that many of the Pearson correlation coefficient values were much higher in the environmental stratification analysis than in the campaign-wide analysis presented in section 4.3. This was interesting to see and, despite the reduced number of comparison data points within each bin due to the stratifications, many of them were statistically significant based on a p-value < 0.01. From an initial cursory check of Fig. 4.5, it can be deduced that most of the 355- and 532-nm AOT comparisons with AMPR CLW yielded negative Pearson correlation coefficients, regardless of the environmental stratification. In contrast, most of the 355-nm backscatter values yielded positive correlations with AMPR CLW, while the remaining HSRL2 parameters generally yielded lower correlation magnitudes under most environmental conditions.

The trend of negative correlations with both AOT datasets but positive correlations with 355-nm backscatter was interesting, as it was hypothesized that most aerosol-concentration parameters would yield similar correlation values, or at least similar correlation magnitudes, with the same remote-sensing convective parameter. The exact reason for this difference was not immediately clear, but since the strongest widespread negative correlations seemed to be largely limited to the AMPR correlations, rather than APR-3 correlations as noted later, it is possible that the failure of AMPR CLW retrievals within deeper convection may have contributed to these negative correlations. That is, while APR-3 $Z_H$ may have increased in scenes with higher AOT,
FIG. 4.5. Pearson correlation coefficient values from comparing AMPR CLW with HSRL2 AOT, extinction (Ext), and backscatter (Bsc) at 355 and 532 nm (top and bottom borders) within environmental bins stratified by the nine AVAPS parameters (left border) at low (L), medium (M), and high (H) magnitudes (right border). AVAPS magnitudes were stratified using the values from Test #2 in Table 4.1. Within each cell, the parenthesized value indicates the number of data points used in the comparison, while an asterisk indicates that the Pearson correlation coefficient’s associated p-value was < 0.01.

Any resulting precipitation formation would have likely caused AMPR CLW to remain relatively low, yielding an unexpected negative correlation with AOT. However, cloud data were excluded from the HSRL2 parameters, so this behavior warrants further investigation. A similar trend across the HSRL2 parameters and environmental bins, albeit with different correlation values and some changes in correlation magnitude, was observed across the sensitivity tests performed, as seen in Appendix B.
To gain a more in-depth look at some of the correlation results in Fig. 4.5, scatterplots were created to visualize the AMPR-HSRL2 correlations in more detail. Of the 54 individual groups of HSRL2 vs AMPR data binned by a given AVAPS parameter, as denoted by the black lines in Fig. 4.5, two will be examined in more detail. A scatterplot of AMPR CLW versus 532-nm backscatter when binned by AVAPS 850–500-hPa LR can be seen on the left side of Fig. 4.6. From Fig. 4.6, the weakly negative correlations between AMPR CLW and HSRL2 532-nm backscatter when 850–500-hPa LR was low to medium (*i.e.*, < 5.43 °C km<sup>-1</sup>) can be seen. However, one LR increased past 5.43 °C km<sup>-1</sup>, there was a tendency for AMPR CLW and HSRL2 532-nm backscatter to be more strongly and positively correlated. Since LR is directly related to environmental instability, this trend suggests that once conditions became more favorable for convection overall (*i.e.*, more conditionally unstable), increases in general aerosol concentration were associated with taller clouds and/or greater cloud liquid water content. These trends match the hypothesized relationship that increases in aerosol concentration would generally lead to higher CLW values by virtue of providing more CCN and favoring the development of deeper convection due to latent heat of condensation.

A similar trend can be seen in the scatterplot of AMPR CLW vs HSRL2 355-nm backscatter when binned by 700-hPa w in Fig. 4.6. As 700-hPa w increased, the positive correlation between AMPR CLW and HSRL2 355-nm backscatter also increased, indicating positive correlation between aerosol concentration and cloud liquid water path. As with the 850–500-hPa LR bins discussed previously, these trends matched expectations that enhanced aerosol concentration would be associated with deeper convection under conditions that were more favorable for convection in general. It is
FIG. 4.6. (Left) scatterplot of maximum AMPR CLW versus HSRL2 532-nm backscatter within scenes binned by AVAPS-derived 850–500-hPa LR. (Right) scatterplot of maximum AMPR CLW versus HSRL2 355-nm backscatter within scenes binned by AVAPS-derived 700-hPa w. AVAPS threshold values were from Test #2 in Table 4.1. In both plots, blue triangles, green circles, and black squares correspond to data points associated with low, medium, and high magnitudes of the associated AVAPS parameter, respectively. Likewise, blue, green, and black lines represent first-order polynomial fits to the data associated with low, medium, and high magnitudes of the associated AVAPS parameter, respectively.

especially noteworthy that all data points in the “high 700-hPa w” category were associated with positive 700-hPa w values with statistical significance, as seen in Table 4.1, which are particularly favorable conditions for convection.

Another interesting trend in the right plot of Fig. 4.6 is the jump in “high” data points, where 355-nm backscatter increased sharply around an AMPR CLW of 1 kg m$^{-2}$. This value has been associated with the transition zone between largely non-precipitating and precipitating clouds (e.g., Jiang and Zipser 2006). The tendency for nearly all observations of backscatter $> 0.5$ Mm$^{-1}$ sr$^{-1}$ (i.e., relatively high aerosol concentrations) to fall along this transition line suggests that these higher concentrations may have supported the development of convection to the point where precipitation began to form. While this was primarily the case when 700-hPa w was “high,” a few backscatter values around 2.5 Mm$^{-1}$ sr$^{-1}$ can also be seen around this transition zone for the “low” 700-hPa w
category. Since the plots in Fig. 4.6 are of maximum AMPR CLW in a given scene, it is possible that this 1 kg m\(^{-2}\) zone stands out as regions where the transition of cloud water into rain water begins to dominate. This makes sense physically, given the favorable environmental conditions for convection and general growth of cloud and rain hydrometeors, though it is unexpected that this trend seems fairly constant with 355-nm backscatter, as it was hypothesized that increased aerosol concentration would hinder the formation of raindrops, all else being equal. It is also noteworthy that numerous “high” 700-hPa w data points with lower aerosol backscatter values were associated with lower AMPR CLW values, further suggesting potential influences from these aerosols. However, it should be stressed that a larger sample size would greatly benefit further examination of this trend, given the influences that a relatively small number of observations exerted on the correlations in the right plot of Fig. 4.6, and it is apparent that a similar trend was not as obvious in the left plot of Fig. 4.6. It is also noteworthy that the trends in Fig. 4.6 were relatively consistent across the sensitivity tests performed, as illustrated in Appendix B.

In addition to these interesting and noteworthy trends, there are other unexpected trends in Fig. 4.5 that should be noted, along with some caveats. Firstly, while some of the patterns seen throughout Fig. 4.5 were constant across the different AVAPS parameters, some correlations changed considerably depending on which parameter was used to stratify the environment (e.g., using \(T_d\) below 1 km AGL compared to using 700–500-hPa LR when examining 355-nm backscatter versus AMPR CLW). While these parameters may represent different environmental conditions, they are both directly related to convection and important to consider in its development and intensity. In
addition, while many trends were fairly constant between HSRL2’s 355- and 532-nm channels for the same AVAPS parameter, some did see a noticeable change in Pearson correlation coefficient between the channels. This differs from the consistency noted in Lenhardt et al. (2022); however, their study focused on consistency in aerosol concentrations between the two channels, whereas this study focused on those concentrations compared with a given remote-sensing parameter, so differences are expected. These inconsistencies for some parameters may be associated to the sensitivities of 355 and 532 nm to different aerosol sizes, with 355 nm more sensitive to smaller aerosols. The negative correlations between the AOT parameters and AMPR CLW were also unexpected, though potentially related to CLW failure in regions of moderate to strong precipitation.

Additionally, most trends in Fig. 4.5, including those shown in Fig. 4.6, were consistent across the four sensitivity tests performed, as shown in Appendix B; however, some did change significantly in their Pearson correlation coefficient, and the magnitude of some correlations appeared to be highly dependent on the AVAPS thresholds used. Lastly, as is true for all analyses discussed in this paper, while high correlation between two parameters is interesting and potentially significant, it does not guarantee a cause-and-effect situation between the two parameters. Thus, the most noteworthy trends identified and discussed in this study (e.g., Fig. 4.6) should continue to be examined in future work to further evaluate their significance and potential influences on convection.
4.4.2 APR-3 Ku-band Results

A similar analysis is presented in this subsection when using Ku-band APR-3 $Z_H$ data as the convective parameters to compare with HSRL2 data under different environmental conditions. As with the AMPR CLW analysis, the figures shown herein utilized the AVAPS thresholds from Test #2 in Table 4.1, with the full sensitivity-test results presented in Appendix B. To begin, the full Pearson correlation coefficient table between APR-3 peak composite $Z_H$ and the HSRL2 parameters can be seen in Fig. 4.7. Several highly positive correlations between APR-3 peak composite $Z_H$ and the HSRL2 parameters resulted from the stratification, especially when environmental lapse rates or K-Index were used as the stratification parameter, though few were statistically significant. Additionally, the prevalence of negative correlation between AOT and the convective parameter noted for the AMPR analysis was not as profound in Fig. 4.7.

The two parameters selected for more in-depth analysis from Fig. 4.7 were: 1) 355-nm backscatter binned by 850–500-hPa LR, and 2) 532-nm extinction binned by 700–500-hPa LR, both of which can be found in the scatterplots in Fig. 4.8. It was interesting to see the switch in correlation sign from negative to positive for the left plot in Fig. 4.8 as lapse rate increased, which may indicate that influence of aerosols on peak $Z_H$ was not as significant until the environment became more favorable for convection in general. This makes sense physically, and the data point (blue triangle) of backscatter > 2.5 Mm$^{-1}$ sr$^{-1}$ associated with a peak $Z_H$ around 30 dBZ is an example of this trend, as a larger peak $Z_H$ might be expected under these aerosol concentrations within a more favorable environment, such as the data point (green circle) which had a similar aerosol concentration but a peak $Z_H$ around 55 dBZ. This largely results from higher aerosol
FIG. 4.7. As in Fig. 4.5, but for the comparison of maximum APR-3 Ku-band composite $Z_H$ with HSRL2 AOT, Ext, and Bsc at 355 and 532 nm within environmental bins stratified using the AVAPS parameters and low-medium-high threshold values from Test #2 in Table 4.1.

concentrations favoring the development of fewer but larger raindrops, which would dominate the $Z_H$ value observed, but also points to the importance of considering the surrounding environment. However, it is also acknowledged that this comparison involves very few data points.

From the right plot in Fig. 4.8, it was noteworthy that the “medium” category of 700–500-hPa LR had a substantially stronger correlation with peak Ku-band $Z_H$ compared to the lower and higher categories when binned by 532-nm extinction, and the
FIG. 4.8. As in Fig. 4.6, but for maximum APR-3 Ku-band composite $Z_H$ versus (left) HSRL2 355-nm backscatter, binned by AVAPS-derived 850–500-hPa LR, and (right) HSRL2 532-nm extinction, binned by AVAPS-derived 700–500-hPa LR.

highest peak $Z_H$ values were associated with extinction values around 0.15–0.40 km$^{-1}$, or a “medium” aerosol concentration in this case. This trend hints at more of a “Goldilocks” zone in aerosol concentration discussed in section 4.1, where too high or too low of a concentration would be detrimental to convective intensity. While the overall trend in these results seems to suggest that higher aerosol concentrations were more favorable for convection (e.g., the few data points with extinction $> 0.5$ km$^{-1}$ around 50–55 dBZ, each within a different 700–500-hPa LR group), it was interesting to see some of these medium-magnitude values stand out. However, as with previous comparisons, the strength of this trend is limited by the relatively small sample size. It was also noteworthy that the environmental lapse rates seemed to stand out as yielding especially strong correlations between the aerosol and convective parameters, which matches the previous AMPR results. However, these correlation interpretations must consider the same limitations and caveats discussed at the end of subsection 4.4.1, which will be revisited in section 4.5. In addition, the trends in Fig. 4.7 were largely consistent across
the sensitivity tests except for Test #1, as seen in Appendix B, where some parameters with weak to moderate positive correlations in the other tests were highly negatively correlated in Test #1; however, in most of these cases, the number of comparison data points was relatively small (around five), which likely had an adverse effect on the resulting correlations.

Next, the number of APR-3 Ku-band composite $Z_H$ pixels > 30 dBZ was used as the convective parameter for the same comparisons, for which the full Pearson correlation coefficient table from Test #2 can be found in Fig. 4.9. It can be seen in Fig. 4.9 that several more highly positive correlations were present compared to Figs. 4.5 and 4.7, which was likely due to Fig. 4.9’s convective parameter focusing on the abundance of convection, defined by Ku-band $Z_H > 30$ dBZ, rather than peak magnitude of $Z_H$ or CLW in a given scene. The strongest positive correlations were found between APR-3 composite $Z_H$ pixels > 30 dBZ and HSRL2 extinction at 355 and 532 nm, especially when the environment was stratified by lapse rate, K-Index, and LCL altitude. Some statistically significant correlations were also found with 532-nm backscatter, but the relatively low correlations with 355-nm backscatter were unexpected.

The correlations of APR-3 composite $Z_H$ pixels > 30 dBZ and HSRL2 532-nm data were examined further via Fig. 4.10, which presents the APR-3 comparison with 532-nm extinction when binned by 850–500-hPa LR and the APR-3 comparison with 532-nm backscatter when binned by K-Index. As with earlier figures, it was interesting to see the strong correlations when the comparisons were binned by 850–500-hPa LR, which may indicate the importance of considering this deeper-layer lapse rate when evaluating aerosol influences on tropical convection. However, the reduced number of
FIG. 4.9. As in Fig. 4.5, but for the comparison of the number of APR-3 Ku-band composite $Z_H$ pixels > 30 dBZ against HSRL2 AOT, Ext, and Bsc at 355 and 532 nm within environmental bins stratified using the AVAPS parameters and low-medium-high threshold values from Test #2 in Table 4.1.

data points in this lapse rate, caused primarily by the P-3 flying below the 500-hPa level when many dropsondes were launched, could have impacted the results, even with the statistical significance of resulting correlations. Despite this reduction in data points, it can be inferred from the left plot in Fig. 4.10 that the correlation between composite $Z_H$ pixels > 30 dBZ and HSRL2 532-nm extinction became more positively correlated as lapse rate increased, which matches the same physical expectations discussed previously, where the higher aerosol concentration may have benefited convection in general as the
FIG. 4.10. As in Fig. 4.6, but for number of APR-3 Ku-band composite $Z_H$ pixels $> 30$ dBZ versus (left) HSRL2 532-nm extinction, binned by AVAPS-derived 850–500-hPa LR, and (right) HSRL2 532-nm backscatter, binned by AVAPS-derived K-Index.

environment became more supportive of convection. However, a greater scattering can be seen across the convective parameter for higher aerosol concentrations in both plots than was observed in Figs. 4.6 and 4.8, which points at some of the uncertainties associated with fully separating aerosol and environmental influences on convection. As noted in this subsection, the selected APR-3 parameter is more sensitive to widespread convection in a given scene, rather than a peak magnitude. Thus, it seems the higher aerosol concentrations supported the development of convection in general within a given scene, whether these APR-3 pixels were part of a single large convective storm or several individual plumes. Two of the three correlations in the left plot of Fig. 4.10 were statistically significant.

Examining the right plot in Fig. 4.10, it can be seen that binning the APR-3 versus HSRL2 comparisons by K-Index also led to highly positive correlations as K-Index increased. This matched the hypothesis that K-Index would be strongly associated with
composite $Z_H$ pixels $> 30$ dBZ in particular, given the K-Index’s association with convection in general, rather than an indication of convective severity (George 1960). This APR-3 product was also strongly associated with HSRL2 extinction when binned by K-Index, as seen in Fig. 4.9, but the focus here is on backscatter given its direct measurement by HSRL2. The correlation between convective abundance and aerosol concentration was near zero when K-Index was low, but became increasingly positive, especially once K-Index increased past 35.61°C. Some of the locally high aerosol concentrations (e.g., $> 0.05$ Mm$^{-1}$ sr$^{-1}$) were associated with a lower number of $Z_H$ pixels $> 30$ dBZ. While the differing scene times in this analysis may have had an effect, this trend further stresses the importance of considering the environment alongside the aerosol concentration (i.e., many of these locally high aerosol concentrations were associated with a “low” K-Index), and suggests that increased aerosol concentration may not have strongly supported convective development within less-favorable environments.

As with peak APR-3 $Z_H$, most correlations in Fig. 4.9 were relatively similar across the sensitivity tests performed, as seen in Appendix B. However, some extinction and backscatter values that were positively correlated with APR-3 when binned by lapse rates in Tests #2 and #3 became negative in Tests #1 and #4, particularly in the “low” group for 850–500 and 700–500 hPa, which suggests that there was considerable spread in the aerosol concentration and/or APR-3 $Z_H$ data within the scenes that fell along the low-medium threshold. Despite these correlations, the same caveats discussed earlier and at the end of subsection 4.4.1 must also be considered, such as the impacts of a relatively small sample number of high correlations and the possibility that a high correlation may
not mean a cause-and-effect situation; these also hold true for the Ka-band analysis in the next subsection.

4.4.3 APR-3 Ka-band Results

This subsection focuses on the same APR-3 convective parameters of peak $Z_H$ and number of pixels $> 30$ dBZ as discussed in the previous subsection, but the analyses herein were performed using Ka-band data. To begin, Fig. 4.11 illustrates the correlations between APR-3 Ka-band peak composite $Z_H$ and the HSRL2 parameters. From Fig. 4.11, many weakly, moderately, and strongly negative correlations can be seen between the APR-3 parameter and the HSRL2 parameters across all environmental bins, which was unexpected. Because Ka-band will become attenuated more quickly than Ku-band in the same storm, it is possible that the Ka-band signal became fully attenuated in some situations before fully capturing the $Z_H$ core. A visual inspection of several scenes (not shown) indicated that this often occurred above regions of high Ku-band $Z_H$. In addition, the onset of non-Rayleigh resonance effects at Ka-band as raindrops form and grow (i.e., diameter larger than approximately 840 μm for the 0.84-cm wavelength) can cause a decrease in $Z_H$ due to a reduction in returned power in this resonance region (e.g., Hogan et al. 2005; Fritz and Chandrasekar 2012), which may have contributed to the unexpected negative correlations. The only statistically significant positive correlation in Fig. 4.11 was found between the APR-3 parameter and HSRL2 355-nm backscatter within a medium 700–500-hPa LR. The other lapse rates and K-Index correlations were largely unexpected, especially those found for comparisons with HSRL2 extinction.
within a high 850–500-hPa LR, which had previously yielded some of the strongest positive correlations.

To examine these trends in more detail, Fig. 4.12 includes scatterplots of peak Ka-band composite $Z_H$ versus 532-nm data, namely comparisons with 532-nm backscatter when binned by 700–500-hPa LR and 532-nm extinction when binned by 850–500-hPa LR. From Fig. 4.12, a very similar pattern can be seen in both plots, where there is a weakly positive correlation for the low category, weakly (left plot) or moderately (right plot) positive correlation in the medium category, and moderate to moderately strong

$$
\begin{array}{cccccccc}
\text{355-nm AOT} & \text{532-nm AOT} & \text{355-nm Ext} & \text{532-nm Ext} & \text{355-nm Bsc} & \text{532-nm Bsc} \\
-0.14 (33) & -0.28 (35) & 0.03 (33) & 0.04 (35) & 0.04 (37) & 0.09 (39) \\
-0.15 (28) & -0.22 (29) & -0.22 (28) & -0.28 (29) & 0.21 (31) & -0.05 (32) \\
-0.07 (20) & -0.18 (24) & 0.22 (20) & 0.22 (24) & -0.25 (24) & -0.08 (28) \\
-0.26 (28) & -0.32 (30) & 0.08 (28) & 0.08 (30) & 0.01 (32) & 0.05 (34) \\
0.00 (29) & -0.21 (32) & -0.04 (29) & -0.06 (32) & 0.08 (33) & 0.10 (36) \\
-0.21 (24) & -0.21 (26) & 0.07 (24) & 0.06 (26) & -0.28 (27) & -0.23 (29) \\
0.10 (12) & -0.69 (12) & -0.31 (12) & -0.30 (12) & -0.14 (14) & -0.56 (14) \\
-0.54 (14) & -0.51 (14) & -0.22 (14) & -0.27 (14) & 0.71 (14)* & 0.54 (14) \\
0.36 (12) & -0.01 (15) & 0.45 (12) & 0.22 (15) & -0.37 (12) & 0.15 (15) \\
-0.19 (11) & -0.81 (11)* & -0.60 (11) & -0.62 (11) & 0.30 (13) & -0.35 (13) \\
-0.23 (14) & -0.06 (15) & 0.14 (14) & 0.18 (15) & 0.24 (14) & 0.45 (15) \\
-0.03 (13) & -0.11 (15) & 0.42 (13) & 0.12 (15) & -0.32 (13) & 0.00 (15) \\
0.09 (24) & -0.03 (29) & 0.12 (24) & 0.10 (29) & 0.02 (24) & 0.10 (29) \\
-0.23 (27) & -0.49 (29)* & 0.03 (27) & 0.04 (29) & 0.07 (30) & 0.08 (32) \\
-0.30 (30) & -0.13 (30) & -0.17 (30) & -0.20 (30) & -0.22 (37) & -0.07 (37) \\
-0.35 (15) & -0.68 (15)* & -0.27 (15) & -0.32 (15) & 0.16 (15) & 0.07 (15) \\
-0.08 (12) & -0.42 (15) & -0.48 (12) & -0.07 (15) & 0.39 (12) & 0.17 (15) \\
-0.36 (11) & -0.22 (11) & 0.25 (11) & 0.25 (11) & 0.26 (13) & 0.33 (13) \\
0.02 (28) & -0.03 (30) & 0.02 (28) & 0.02 (30) & 0.04 (31) & -0.06 (33) \\
-0.19 (21) & -0.38 (24) & -0.15 (21) & -0.11 (24) & 0.08 (24) & -0.07 (27) \\
-0.29 (32) & -0.34 (34) & 0.09 (32) & 0.06 (34) & 0.11 (37) & 0.10 (39) \\
-0.10 (32) & -0.28 (35) & -0.04 (32) & -0.00 (35) & 0.13 (34) & 0.14 (37) \\
-0.09 (26) & -0.14 (28) & -0.32 (26) & -0.32 (28) & -0.01 (27) & -0.43 (29) \\
-0.23 (23) & -0.22 (25) & 0.03 (23) & -0.08 (25) & 0.08 (31) & -0.22 (33) \\
-0.10 (22) & -0.23 (25) & 0.23 (22) & 0.20 (25) & -0.08 (28) & 0.16 (31) \\
-0.15 (30) & -0.27 (33) & -0.07 (30) & -0.08 (33) & -0.12 (33) & -0.17 (36) \\
-0.07 (29) & -0.15 (30) & -0.06 (29) & -0.04 (30) & -0.23 (30) & 0.16 (31) \\
\end{array}
$$

FIG. 4.11. As in Fig. 4.7, but for maximum APR-3 Ka-band composite $Z_H$.
negative correlation for the high category. Since the scenes for the Ka-band analyses were the same as Ku band in terms of space and time coverage, it seems plausible that significant attenuation above the center of each storm, combined with non-Rayleigh resonance effects within raindrop regions, contributed to the negative correlations in Fig. 4.12.

Since more vigorous convection would be expected to yield a taller storm and higher peak $Z_H$ in its core, all else being equal, it would make sense that the Ka-band data would become attenuated more quickly and that hydrometeors would grow large enough to be in non-Rayleigh resonance at Ka-band. If the convection was invigorated by higher aerosol concentrations as hypothesized, the upper-left data point and two lower-right data points in the right plot of Fig. 4.12 make sense since, within favorable environmental conditions, the stronger convection in the higher-aerosol-concentration case (i.e., extinction > 1.1 km$^{-1}$; the upper-left point) would yield a lower observed peak $Z_H$ due to severe attenuation and/or resonance effects, whereas the more pristine environments (i.e.,
extinction < 0.2 km\(^{-1}\); the lower-right points) would be associated with shallower convection, allowing the Z\(_H\) core to be observed prior to attenuation and/or may contain a raindrop size distribution that fell within the Rayleigh scattering regime at Ka band. That being said, the peak Z\(_H\) observed in the low-aerosol-concentration cases of the lower-right points was significant at 55–65 dBZ, indicating that large raindrops formed in these scenes. The same trends hold true for the left plot in Fig. 4.12.

As shown in Appendix B, these trends were fairly consistent across the sensitivity tests performed, with most of the environmental bins yielding negative correlations between the APR-3 and HSRL2 parameters. The main exception was comparisons with HSRL2 extinction within scenes of high 850–700-hPa LR, which switched from weakly positive in Tests #2 and #4 to moderately strongly negative in Tests #1 and #3, suggesting that there may have been a clustering of data points right around a low-level lapse rate value of 5.2 °C km\(^{-1}\).

Next, comparisons using number of APR-3 Ka-band pixels with composite Z\(_H\) > 30 dBZ was used as the convective parameter, the correlation table for which is presented in Fig. 4.13. The correlation trends in Fig. 4.13 were very different from those in Fig. 4.11, with most environmental bins yielding positive, some strong and statistically significant, correlations between the APR-3 and HSRL2 parameters. This was likely because, as stated previously, this APR-3 parameter focuses on the abundance of convection within a scene in general. Thus, shallower and weaker storms with lesser attenuation may have had more of their vertical extent captured by the Ka-band data and/or may have contained smaller (\textit{i.e.}, Rayleigh-scattering) raindrops. Fig. 4.13 is also strikingly similar to Fig. 4.9, with the strongest correlations found when comparing
FIG. 4.13. As in Fig. 4.9, but for number of APR-3 Ka-band composite $Z_H$ pixels > 30 dBZ.

APR-3 against HSRL2 extinction within environments binned by lapse rate, K-Index, and LCL altitude.

The comparisons illustrated in more detail are: 1) APR-3 comparison with 532-nm extinction when binned by 850–500-hPa LR, and 2) APR-3 comparison with 532-nm backscatter when binned by K-Index, which are the same as previously analyzed in Fig. 4.10 and can be found in Fig. 4.14. Comparing Figs. 4.10 and 4.14, it can be seen that both pairs of plots are very similar, especially the left plot in each figure. That is, in Fig. 4.14, the increasing and highly positive correlation between the APR-3 and HSRL2
parameters with increasing 850–500-hPa LR can be seen in the left plot. This matched the physical expectations discussed previously, where aerosol concentrations may increasingly invigorate convection as the environment becomes more unstable. Likewise, the right plot in Fig. 4.14 indicates a correlation shift from negative values at low K-Index to moderately strong positive correlations at high K-Index values. This matches the expectation that the K-Index would serve as a general indicator of convective potential, while increasing aerosol concentrations would lead to development of more widespread convection within favorable environments. These trends, given their similarity with those for the Ku-band plots, also demonstrate how severe attenuation and/or non-Rayleigh resonance seemed to affect the comparisons with maximum composite $Z_H$ in Fig. 4.12 more so than those for widespread convection in Fig. 4.14. Future work would benefit from applying a more enhanced attenuation correction method than the simple one tested in this study, as briefly mentioned in chapter 3.
From the sensitivity-test trends in Appendix B, most of the comparisons were fairly similar across the range of values tested. However, there were considerable deviations in the APR-3 versus HSRL2 parameters when binned according to 850–500- and 700–500-hPa LRs, especially those binned according to high 850–500-hPa LR. These changes may have resulted from the smaller 500-hPa dataset due to P-3 altitude.

4.5 Summary of Expanded Environmental and Aerosol Analyses

The purposes of this chapter were to: 1) expand the science applications of AMPR’s geophysical retrievals by utilizing them in addressing CAMP²Ex science questions, and 2) explore the impacts of aerosol concentrations on various parameters related to convective intensity using remote-sensing datasets. Initial analyses were performed by comparing nine AVAPS dropsonde parameters with three AMPR and APR-3 parameters related to convective intensity and/or frequency across 144 dropsondes from CAMP²Ex SFs 05–19. Each dropsonde was associated with the corresponding APR-3 scan at its launch time, whose file start and end times were used to develop a “scene” for all comparisons associated with the given dropsonde. The three convective parameters used were: maximum AMPR CLW, maximum APR-3 Ku-band composite Z₄₄, and number of APR-3 Ku-band composite Z₄₄ pixels > 30 dBZ. The nine AVAPS-derived parameters were: 700-hPa w; modified CAPE; LCL altitude; K-Index; lapse rates between the 850–700-, 850–500-, and 700–500-hPa levels; mean Tₛ below 1 km AGL; and mean Tₛ below the 925-hPa level. Comparisons were made using Pearson and Spearman correlation coefficient values. The results of these comparisons indicated little correlation between the convective parameters and AVAPS parameters.
when examined across the entire CAMP$^2$Ex campaign, with only the 850–700-hPa LR yielding a correlation magnitude > 0.40, and this correlation was unexpectedly negative. Many limitations in the dataset, such as the P-3 avoiding the most intense convection during a given flight and environmental modification from nearby convection, and the selected analysis approach, such as assuming that AMPR CLW would generally increase by a significant amount immediately before its failure at the edges of all precipitation regions, likely affected these results.

A second analysis was then performed where the three aforementioned AMPR and APR-3 convective parameters, in addition to Ka-band peak composite $Z_H$ and number of Ka-band composite $Z_H$ pixels > 30 dBZ, were compared with HSRL2 backscatter, extinction, and AOT at 355 and 532 nm within environments that were binned according to different magnitudes for each of the nine AVAPS parameters. For each AVAPS parameter, threshold values were selected to divide the scenes into “low,” “medium,” and “high” values for the given parameter, and a sensitivity test was performed where four different sets of threshold values were tested for each AVAPS parameter. Within each of these environmental bins, the convective parameter and HSRL2 parameter were analyzed using Pearson and Spearman correlation coefficients.

The results of this environmental stratification analysis of aerosol concentration impacts on convective intensity and frequency were much more fruitful, with many strongly positive and negative correlations observed. A particularly noteworthy environmental stratification parameter was 850–500-hPa LR, which yielded notable results for all five convective parameters, while K-Index and 700–500-hPa LR each appeared in two of the five comparisons; however, selection of these parameters for more
in-depth analysis was subjective, and a full description of the correlation results in each sensitivity test was provided. Comparisons of HSRL2 data with maximum APR-3 Ka-band composite $Z_h$ gave widespread and unexpected negative correlations for nearly all environmental bins, which appeared to be the result of severe attenuation just above the center of stronger storms and non-Rayleigh resonance effects in regions with relatively large raindrops.

For the other four parameters, it was generally observed that correlations between HSRL2 and the convective parameter became more highly positive and occasionally statistically significant as the environmental conditions became more favorable for convection. In other words, aerosol effects on convection were not as significant until the environment was initially supportive of convection in many cases. These results suggest that increased aerosol concentrations may have contributed to stronger and/or more widespread convection, especially once the environmental conditions were favorable for the development of such convection. These results match the hypotheses posed at the outset of this study. However, a few trends hinted at the benefits of a “Goldilocks” zone in terms of aerosol concentration, as demonstrated in past modeling studies, where a medium level of aerosol concentration would be most favorable for convective intensity and/or frequency compared to low and high concentrations. The results herein also stress the importance of considering environmental conditions alongside aerosol concentrations when evaluating impacts on convection.

While many of these results were encouraging, several limitations must be taken into consideration when interpreting them. For example, the number of dropsondes that were launched when the P-3 was above the 500-hPa level was limited, reducing the
dataset for any environmental parameters that make use of 500-hPa data. Second, there were differences in the duration of a given “scene,” which was often 2–12 minutes, but this discrepancy may have affected the comparisons since lower durations were at a disadvantage for observing stronger and more widespread convection compared to longer observation times. There was also some ambiguity regarding whether an increase in the number of composite $Z_H$ pixels $> 30$ dBZ was associated with the same updraft or multiple updrafts across a given scene, which have different implications for convective intensity and frequency. In addition, while many of the correlations in this study were strong and encouraging, they do not necessarily prove a cause-and-effect situation for their respective comparison. Due to these limitations and considerations, it is not possible to say with certainty that increased aerosol concentrations enhanced convection in these CAMP$^2$Ex scenes, but rather the data suggest the possibility for this aerosol enhancement of convection, and further analyses are necessary to increase confidence in the results and conclusions.

Given the encouraging nature of many comparisons in this study, while also considering the above limitations, future work would greatly benefit these science questions. Future efforts could look at addressing the limitations above as much as possible, such as creating constant scene times across CAMP$^2$Ex, using an advanced APR-3 $Z_H$ attenuation correction method, breaking apart the data into those where the composite $Z_H$ pixels $> 30$ dBZ were adjacent or separated by some distance, and further examining other datasets to increase reliability of the strongest correlations observed in these analyses. In addition to the P-3, instruments from the Stratton Park Engineering Company Learjet-35 aircraft that participated in CAMP$^2$Ex could also provide useful in
situ observations around the same time as the P-3’s remote-sensing observations to confirm aerosol concentration. Including AMPR’s other geophysical retrievals might provide useful information. Future work might also consider examining other aerosol properties, such as type and composition, to infer the role their hygroscopicity may have played in serving as effective CCN across the different scenes analyzed. Other remote-sensing datasets, such as satellite data, might be useful in describing the strength of convection sampled by the P-3 versus the peak convection that was present just outside of a given scene. Additional environmental parameters related to convection might be useful to examine. Lastly, peak height of the 30-dBZ $Z_{HL}$ contour within a given storm would be an important convective parameter to consider when evaluating updraft strength, and should be incorporated into any future expansions of this work.
Chapter 5. Summary, Conclusions, and Future Work

5.1 Summary and Conclusions

This doctoral dissertation provided a detailed description of the development, testing, and validation of CLW, WV, and WS retrievals using polarization-deconvolved $T_b$ from the upgraded AMPR system. Derivations and initial evaluations were performed against simulated GDAS atmospheric profiles, while independent retrievals from 1DVAR using data collected from the OLYMPEX/RADEX field campaign were employed alongside AVAPS dropsondes to test the resulting retrievals. To expand the geographical and climatological applicability of these retrievals, they were incorporated into CAMP$^2$Ex. The CLW retrieval methods required additional modification to account for the high water vapor content in the maritime tropics, while WS retrievals were slightly updated to account for effects of the new AMPR radome used during CAMP$^2$Ex. Validation of WV and WS retrievals was greatly expanded using dropsonde data during CAMP$^2$Ex, while CLW retrievals were validated using multiple independent remote-sensing retrievals. These validated methods were then applied to CAMP$^2$Ex science questions related to the onset of accretion and/or freezing within tropical convection, the response of airborne remote-sensing parameters to variations in several environmental conditions related to convective intensity and/or frequency, and influences of aerosol concentrations on maritime tropical convection when examined under different
environmental constraints and magnitudes. A synopsis of the key results from each chapter is provided below.

Chapter 2 detailed the following performance statistics for CLW, WV, and WS when compared against simulated GDAS profiles:

- **CLW**: nearly unbiased mean retrieval error; minimal crosstalk error with WV, WS, and SST apart from WV > 30 kg m\(^{-2}\); mean retrieval RMSD of 0.11 kg m\(^{-2}\); and median MedAD of 2.26 x 10\(^{-2}\) kg m\(^{-2}\).

- **WV**: mean retrieval error near 0 kg m\(^{-2}\) for WV < 50 kg m\(^{-2}\); virtually no crosstalk errors with CLW, WS, and SST; mean retrieval RMSD of 1.28 kg m\(^{-2}\); and median MedAD of 0.22 kg m\(^{-2}\).

- **WS**: negative retrieval errors for WS < 5 m s\(^{-1}\) and WS > 15 m s\(^{-1}\), but positive retrieval errors for WS of 5–15 m s\(^{-1}\), with mean error magnitude < 1 m s\(^{-1}\) for WS between 3–19 m s\(^{-1}\); little crosstalk error apart from SST between 0–3°C, where mean error magnitudes were still < 1 m s\(^{-1}\); mean retrieval RMSD of 1.11 m s\(^{-1}\); and median MedAD of 0.55 m s\(^{-1}\).

Comparisons with independent 1DVAR retrievals throughout OLYMPEX/RADEX indicated that both methods yielded similar results in clear air, but the new retrieval equations presented herein attempted to retrieve in precipitation regions, whereas 1DVAR retrievals generally failed in these regions. The median RMSD values for CLW, WV, and WS assuming 1DVAR values were “truth” were 9.95 x 10\(^{-2}\) kg m\(^{-2}\), 2.00 kg m\(^{-2}\), and 2.35 m s\(^{-1}\), respectively, with respective median MedAD of 2.88 x 10\(^{-2}\) kg m\(^{-2}\), 1.14 kg m\(^{-2}\), and 1.82 m s\(^{-1}\). Two approaches were used in dropsonde validation of WV and WS to account for AMPR and AVAPS being flown on separate aircraft during
OLYMPEX/RADEX, which yielded WV MedAD of 2.10 and 1.80 kg m\(^{-2}\) at the time and location of AVAPS minimum height, respectively, with respective WS MedAD of 1.15 and 1.53 m s\(^{-1}\). Therefore, mean AVAPS MedAD for WV (WS) was 1.95 kg m\(^{-2}\) (1.34 m s\(^{-1}\)) from the nine dropsondes examined, which agreed well with uncertainties from past studies. The ability to identify gust fronts from WS retrievals was also highlighted.

In chapter 3, it was shown that the new tropical CLW retrieval method, developed to remove residual CLW > 0 kg m\(^{-2}\) in clear air, greatly improved the retrieval equation’s performance. In addition to removing much of the residual CLW, clear-air cross-track variability in the retrievals was significantly reduced, and excellent error statistics were recorded from comparisons with the same GDAS profiles examined in chapter 2, namely: RMSD of 1.94 x 10\(^{-2}\) kg m\(^{-2}\); mean retrieval error of 1.90 x 10\(^{-3}\) kg m\(^{-2}\); and crosstalk errors with WV, WS, and SST of 1.37 x 10\(^{-2}\), 3.60 x 10\(^{-3}\), and 4.79 x 10\(^{-4}\) kg m\(^{-2}\), respectively. Minor cross-track artifact corrections to the WS retrievals offered slight improvements compared to chapter 2, with a mean difference of 1.76 m s\(^{-1}\) against 144 AVAPS CAMP\(^2\)Ex dropsondes. Mean WV difference between AMPR’s retrievals and these same dropsondes was 8.27%. Both WV and WS mean differences were within target uncertainties.

Validation of CLW was more difficult than anticipated and highlighted several issues with comparing retrievals from two airborne datasets down to the fraction of a second. Initial comparisons with APR-3 Ka-band CLW, applied by integrating LWC obtained from a z-LWC relationship, yielded a 0.432 kg m\(^{-2}\) MedAD, 85.7\% median percentage deviation, and -7.02 x 10\(^{-2}\) kg m\(^{-2}\) median bias. The unexpectedly high absolute deviation may have been influenced by residual data artifacts, especially regions
with raindrops that were missed by precipitation masking, and a potential lack of Ka-band sensitivity to smaller cloud droplets despite relatively low percentage deviation and bias. However, use of a CLW-specific retrieval method from RSP resulted in a much lower MedAD of $8.08 \times 10^{-2}$ kg m$^{-2}$, favorable median percentage deviation of 86.0%, and median bias of $-3.28 \times 10^{-2}$ kg m$^{-2}$. To address the specific science questions posed in chapters 1 and 3 that were answered:

1) What trends are present in AMPR’s tropical geophysical retrievals, and how do they compare with expectations based on prior studies?
   - **Answer**: AMPR’s mean CLW, median WV, and median WS outside of precipitation-flagged regions were 0.07 kg m$^{-2}$, 49.7 kg m$^{-2}$, and 5.63 m s$^{-1}$, respectively. These were similar to values observed in past studies, which matches the hypothesis.

2) What information can AMPR’s cloud liquid water (CLW) retrievals provide about cloud and precipitation processes?
   - **Answer**: Expected relationships, namely CLW $\propto (CTH)^2$, were observed for RSP-derived CTH < 4 km AMSL. However, once CTH increased beyond 4 km, there was a sudden decrease in CLW, even outside of contamination from altostratus clouds. This may have indicated the onset of significant accretion and/or freezing once CTH increased past 4 km. The relationship observed for CTH < 4 km matches the hypothesis, but the unexpected trends observed for CTH > 4 km were interesting and potentially important.

3) What relations can be found between AMPR’s retrievals and dropsonde data on a flight-by-flight basis, and what are their physical explanations?
• **Answer:** AVAPS-derived environmental 0°C level height was found to be moderately correlated with AMPR CLW and WS at 0.49 and 0.43, respectively, during an initial analysis, which may be associated with the prominence of warm-rain processes in the maritime tropics.

Chapter 4 expanded upon the AVAPS analyses introduced at the end of chapter 3. Nine dropsonde parameters with direct implications for convective intensity and/or frequency were compared with AMPR and APR-3 parameters related to convective intensity and/or frequency across 144 CAMP²Ex scenes. The nine dropsonde parameters were: 700-hPa w; modified CAPE; LCL altitude; K-Index; lapse rates between the 850–700-; 850–500-; and 700–500-hPa levels; mean Tₐ below 1 km AGL; and mean Tₐ below the 925-hPa level, while the three remote-sensing convective metrics were: maximum AMPR CLW; maximum APR-3 Ku-band composite Z_H; and number of APR-3 Ku-band composite Z_H pixels > 30 dBZ.

Initial results indicated weak Pearson and Spearman correlation coefficients between the dropsonde and remote-sensing parameters, with 850–700-hPa LR yielding the only correlation magnitude > 0.40, which was unexpectedly negative and likely affected by limitations in the P-3 flight path (i.e., avoiding the most intense convection), environmental modification from nearby convection, and the analysis approach (i.e., AMPR CLW retrievals failing within precipitation). A second analysis was performed, where each remote-sensing parameter, in addition to Ka-band peak composite Z_H and number of Ka-band composite Z_H pixels > 30 dBZ, were compared with cloud-screened backscatter, extinction, and AOT at 355 and 532 nm from HSRL2 within AVAPS-stratified environmental bins. Four sensitivity tests were performed to vary the
thresholds selected to separate each of the nine AVAPS parameters into “low,” “medium,” and “high” categories.

Within these environmental bins, defined by a single AVAPS parameter and magnitude, much higher Pearson and Spearman correlations were observed between the remote-sensing parameters and HSRL2 aerosol variables. Stratifications using 850–500-hPa LR, 700–500-hPa LR, and K-Index were subjectively identified as yielding some of the strongest correlations between the convective and aerosol parameters. Generally, correlations between the HSRL2 and convective parameters became more highly positive and occasionally statistically significant as environmental conditions became more favorable for convection, suggesting that increased aerosol concentrations may have contributed to stronger and/or more widespread convection once environmental conditions were especially favorable for convection. However, some trends indicated that a medium aerosol concentration might be more favorable for convection enhancement than high or low aerosol concentrations (i.e., a “Goldilocks” zone in aerosol concentration). The results also emphasized the importance considering environmental conditions alongside aerosol concentrations when evaluating impacts on convection.

These differences highlight the difficulties in isolating aerosol influences on convection in general, and several limitations in the analyses (e.g., unexpected widespread negative correlations in the maximum Ka-band $Z_H$ analyses, likely due to attenuation and/or non-Rayleigh resonance effects; a reduced number of dropsondes that captured the 500-hPa level; differences in the duration of each scene, though often 2–12 minutes; ambiguity in whether $Z_H$ pixels > 30 dBZ were adjacent or spatially offset, etc.) restrict the ability to state definitive conclusions of aerosol influences on maritime
Further, correlation does not guarantee a cause-and-effect relationship between two variables. Thus, while the results herein are potentially impactful and important to consider, future analyses must continue to investigate the potential enhancement of medium-to-high aerosol concentrations on convection to increase confidence in the results. Answers to the science questions posed in chapters 1 and 4 are as follows:

4) How do radiometer- and radar-based metrics of storm intensity and frequency vary with different dropsonde-measured environmental indicators of convective intensity and/or potential throughout CAMP\textsuperscript{2}Ex?

- **Answer:** weak correlations were observed between most convective metrics and dropsonde parameters when analyzed across CAMP\textsuperscript{2}Ex as a whole, which likely resulted from limitations in the dataset and approach. The 850–700-hPa temperature lapse rate yielded the only moderate correlation, though it was unexpectedly negative. This goes against the hypothesized relationships.

5) When binned into similar environmental groups, how do the same radar- and radiometer-based metrics of storm intensity and frequency vary with lidar-based observations of aerosol concentration?

- **Answer:** Much stronger correlations were observed in this analysis, with trends indicating medium-to-high aerosol concentrations were correlated with higher convective intensity and/or frequency once environmental conditions became more favorable for convection. This matches the hypothesized relationships, but the limitations of this analysis must be considered when interpreting these results.
5.2 Future Work

The results of this dissertation set the stage for many ongoing and potential future analyses, several of which were detailed at the ends of chapters 2, 3, and 4, and will be summarized here. Artifacts observed in the 1DVAR WS retrievals could be investigated further, and an artificial neural network might provide additional insight into the performances of AMPR’s retrieval equations. Additional OLYMPEX/RADEX cases should be included in all analyses, along with AMPR data from IPHEx and IMPACTS. In situ (e.g., Stratton Park Engineering Company Learjet-35 cloud probes during CAMP$^2$Ex) validation of CLW retrievals could be helpful to revisit, despite difficulties in matching observations from these datasets spatiotemporally. Further remote-sensing validation of AMPR CLW would also be interesting, given the limitations associated with the radar comparisons herein, despite the excellent performance against RSP CLW. The potential accretion/mixed-phase identification in AMPR-CLW/RSP-CTH trends should be revisited in greater detail. Including modeling data to fill gaps in the observational data might be especially useful. The development of other AMPR retrievals (e.g., surface rain rate) could provide valuable information, especially in precipitation regions where the CLW retrievals failed.

When considering these results in future analyses of aerosol concentrations and maritime tropical convection, using constant scene times across CAMP$^2$Ex could be beneficial. For the APR-3 $Z_H$ data, applying more advanced attenuation-correction methods than those tested herein would be important, especially at Ka band, as would identifying scenes where the composite $Z_H$ pixels $> 30$ dBZ were adjacent or spatially separated (e.g., by several km). Examining peak height of the 30-dBZ $Z_H$ contour within
a given storm could be highly beneficial. Future work should include AMPR’s other geophysical retrievals in the convective analyses, such as increased surface WS in association with gust fronts. Considering aerosol composition in different CAMP²Ex scenes might provide insight about their ability to serve as effective CCN. Additional dropsonde parameters should be considered in the environmental stratification analysis, and including satellite data might assist with properly describing the overall strength of convection around a given CAMP²Ex scene, especially if not fully captured by the P-3.
References


Appendix A. Additional Information from AMPR CLW Retrieval Validation

This appendix presents details of AMPR’s CLW retrieval validations beyond those discussed in chapter 3. Several new candidate CLW equations were originally developed following the methods of Amiot et al. (2021) and compared against cloud liquid water path from the same 523,176 globally distributed GDAS atmospheric profiles. Total precipitable water, 10-m wind speed, and SST were also obtained from the GDAS data. A total of six “finalist” equations were selected based on their low retrieval and crosstalk errors with WV, WS, and SST, and were further evaluated using CAMP2Ex observations. The equation that offered the lowest retrieval and crosstalk errors and most uniform cross-track clear-air CLW (i.e., Eq. 19, the retrieval coefficients for which are shown in Fig. A.1) was selected, despite slight residual clear-air CLW > 0 kg m\(^{-2}\). To correct this residual CLW, the masks discussed in section 3.2 were applied to all AMPR pixels and mean CLW in the unmasked pixels was subtracted from all AMPR pixels throughout the given SF (Fig. A.2). Pixels with CLW < 0 kg m\(^{-2}\) resulting from this correction were manually set to 0 kg m\(^{-2}\). An additional test (not shown) compared Eq. 19 to the other five “finalist” equations in clear air and clouds (delineated using an AMPR \(T_b\) threshold method). Results indicated that Eq. 19 consistently yielded higher CLW than the other equations, both in clouds and clear air. Therefore, the values in Fig. A.2 were subtracted from all unmasked AMPR pixels in the corresponding flight. The third panel of Fig. 3.2 in chapter 3 demonstrates this correction, where virtually all residual clear-air CLW was removed.
Comparing Eq. 19 with Amiot et al. (2021), including three primary components improved tropical CLW retrievals: 1) 37.1-GHz $T_b$; 2) linear equation elements; and 3) a background SST value. AMPR’s 37.1-GHz channel is more capable of viewing deeper into a given cloud compared to 85.5 GHz while also being more susceptible to attenuation compared to 19.35 GHz, thus providing a more complete vertical cloud profile compared to solely using 19.35 and 85.5 GHz. Introducing linear elements in Eq. 19, alongside nonlinear elements already present, was an attempt to better model the highly nonlinear relations between microwave $T_b$ and CLW (Wilheit and Chang 1980). The tendency of Eq. 19 to fail in heavier precipitation due to precipitation not being included in Eq. 19’s forward model (Amiot et al. 2021) was also observed in CAMP²Ex.

The following QC was applied to all APR-3 Ku- and Ka-band data for validation: 1) remap to Earth-centric coordinates, rather than aircraft-centric coordinates; 2) mask range gates containing noise or missing data; and 3) remove pixels near the ocean surface.
FIG. A.2. Bar plot of mean masked clear-air CLW values from SFs 05–19. These values serve as the correction factors for Eq. 19, and were subtracted from all unmasked pixels in their corresponding SF to yield the final CLW dataset.

wherein $Z_H$ increased considerably due to range-/sidelobe effects (Liu and Zipser 2013). To mask noisy pixels, a 3x3 median filter (i.e., 3 down-range gates by 3 subsequent nadir gates) was run on nadir $V_r$; if standard deviation within the 3x3 grid was greater than 5 m s$^{-1}$, all nine gates were flagged for the associated frequency and subsequently masked. After numerous sensitivity tests, all along-track nadir gates at a given range were masked during a given time period if: 1) along-track Ku-band $Z_H$ standard deviation was less than half the median along-track Ku-band $Z_H$ during the time period, due to relatively consistent $Z_H$ within the range-/sidelobe effects over time; 2) the 10th percentile of Ku-band $V_r$ magnitude was less than the median Ku-band surface $V_r$ calculated in APR-3’s data processing (Durden et al. 2020), due to relatively consistent $V_r$ within the range-/sidelobe effects over time; and 3) the along-track data were within 1 km of the surface range gate flagged by APR-3’s data processing during the first scan in the time period.
This method was deemed most effective in masking near-surface range-/sidelobe effects with relatively few misses or incorrectly flagging other data (e.g., stratiform precipitation). Once masked, a final 9x9 median filter was run through all nadir data to remove any pixels missed by previous steps. During the analyses performed in chapter 4, the above methods were run for all 25 APR-3 cross-track scan positions during each SF.

In Fig. A.3, overall CLW median absolute deviation against Ku-band “truth” CLW was 0.410 kg m\(^{-2}\), with a median percentage deviation of 3.39 \(\times 10^3\)% and median bias of -0.155 kg m\(^{-2}\) (i.e., AMPR biased high relative to APR-3). These values are relatively high for CLW, especially compared with the 0.11 kg m\(^{-2}\) theoretical uncertainty in Amiot et al. (2021) and strong agreement between Eq. 19 and GDAS profiles. Several limitations of these validation methods may have contributed to the relatively high deviations. First, Eq. 16 was not specifically designed for Ku band (Hagen and Yuter 2003), unlike the Ka-band method (Oh et al. 2018). While cloud droplets fall into the Rayleigh scattering regime at Ku band, any unmasked precipitation or cloud-to-precipitation transition regions may have led to considerably higher \(Z_H\) (and, consequently, CLW) due to non-Rayleigh resonance effects. As in Fig. 3.5, a total of 112 comparison data points in Fig. A.4 had an AMPR CLW value > 1 kg m\(^{-2}\), indicating that as much as ~12.5% of the validation dataset may have been affected by unmasked raindrops. The underestimation of Ku-band CLW may have also resulted from Eq. 16 originally being derived for raindrops with diameter > 0.2 mm (Hagen and Yuter 2003). Second, APR-3 data were not corrected for attenuation effects by default, which may have contributed to biases and deviations. Third, regions of relatively small CLW, such as \(O(10^3)\) kg m\(^{-2}\) or less, may have drastically affected percentage deviations, with very
small differences in AMPR CLW and APR-3 CLW at these low values yielding very high percentage deviations.

In addition, the minimum detectable $Z_H$ of -6 to 6 dBZ 3–7 km down range from the radar for Ku band (Dzambo et al. 2019) may have affected detection of certain cloud regions and contributed to the observed deviations. Lastly, several difficulties were encountered when using two airborne remote-sensing instruments for validation that likely contributed to the deviations and biases, such as: correctly matching AMPR and APR-3 observations down to the fraction of a second within a cloud, slight differences in footprint resolution, loss of many coincident observations due to issues with one or both datasets (e.g., noise, aircraft maneuvers, masking during QC, etc.), and other residual data artifacts. The Ku-band histogram (Fig. A.4) maxima fell farther from the one-to-one
FIG. A.4. Two-dimensional histogram comparing AMPR CLW with APR-3 Ku-band CLW for all unmasked nadir data points wherein AMPR, Ku-band, and Ka-band observations were simultaneously available during SFs 05–19. Logarithmic scales are applied to each axis. The number of coincident observations (n) and Pearson correlation coefficient (r) are displayed, and the red dashed line denotes a one-to-one ratio.

ratio line than Ka band did (Fig. 3.5). However, a decreased range of observed Ku-band CLW compared to Ka band resulted in a higher correlation coefficient of 0.40 with AMPR CLW.
Appendix B. Sensitivity Tests of Aerosol versus Convective Parameters

This appendix contains supplemental information for the sensitivity tests that were conducted in section 4.4. In the following figures (i.e., Figs. B.1–B.10), Pearson and Spearman correlation coefficient tables, similar to the correlation tables in section 4.4, are presented for all four sensitivity tests of a given convective metric compared with the HSRL2 aerosol parameters across the AVAPS environmental stratifications. The five correlation tables shown in section 4.4 are repeated here in their respective figures. No scatterplots are presented in this appendix, as the purpose is to provide a full and complete presentation of the correlation analyses performed in section 4.4, rather than additional in-depth analyses of specific correlations.
FIG. B.1. Tables of Pearson correlation coefficient values from comparing AMPR CLW with HSRL2 AOT, extinction (Ext), and backscatter (Bsc) at 355 and 532 nm (top and bottom borders) within environmental bins stratified by the nine AVAPS parameters (left borders) at low (L), medium (M), and high (H) magnitudes (right borders). Within each cell, the parenthesized value indicates the number of data points used in the comparison, while an asterisk indicates that the Pearson correlation coefficient’s associated p-value was < 0.01. The four different tables result from the four different sensitivity tests detailed in Table 4.1, with (upper left) Test #1, (upper right) Test #2, (lower left) Test #3, and (lower right) Test #4 presented herein.
As in Fig. B.1, but for Spearman correlation coefficients.
FIG. B.3. As in Fig. B.1, but for comparisons of maximum APR-3 Ku-band composite $Z_{HI}$ with the HSRL2 parameters.
FIG. B.4. As in Fig. B.3, but for Spearman correlation coefficients.
FIG. B.5. As in Fig. B.1, but for comparisons of the number of APR-3 Ku-band composite $Z_H$ pixels $>30$ dBZ with the HSRL2 parameters.
FIG. B.6. As in Fig. B.5, but for Spearman correlation coefficients.
FIG. B.7. As in Fig. B.3, but for maximum APR-3 Ka-band composite $Z_H$.
FIG. B.8. As in Fig. B.7, but for Spearman correlation coefficients.
FIG. B.9. As in Fig. B.5, but for APR-3 Ka-band composite Q4 pixels > 30 dBZ.
As in Fig. B.9, but for Spearman correlation coefficients.