

Factual Report – Attachment 2

Email correspondence and attachment regarding the RadIA algorithm.

METEOROLOGY

ERA24FA209

*Submitted by: Mike Richards
NTSB, AS-30*

Michael Richards

Subject: RE: Radar interpretation of crash

From: Scott Ellis [REDACTED]@ucar.edu>
Sent: Wednesday, June 26, 2024 2:17 PM
To: Michael Richards [REDACTED]@ntsb.gov>
Cc: Alex Rugg Stebbins <[REDACTED]@ucar.edu>
Subject: Re: Radar interpretation of crash

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Hi Mike,

I will try to answer your questions imbedded below.

On Wed, Jun 26, 2024 at 11:23 AM Michael Richards [REDACTED]@ntsb.gov> wrote:

Sorry one more question after having read a bit more of the article.

- It appears that “mixed phase” could contain either large or small SLW drops, and it is not possible to discriminate what size drops exist within a “mixed phase” signal, is that correct? I.E., we could have large and/or small drops in mixed phase, even though the radar algorithm did not support either large or small drop cases (but those consider environments with just SLW and not when ice crystals are present).

It is true that the algorithm cannot distinguish small and large drops in mixed conditions. The freezing drizzle and small drop icing algorithms are looking for pure freezing drizzle and pure small drops, so the results aren't relevant to the mixed phase results. So you are right, there could have been large drops or small drops present. We looked into discriminating large and small drops in mixed phase, but more work is needed on that.

Am I on right track here?

Thank for any help here,

Mike

From: Michael Richards [REDACTED]@ntsb.gov>
Sent: Wednesday, June 26, 2024 12:13 PM
To: Scott Ellis [REDACTED]@ucar.edu>; Alex Rugg Stebbins [REDACTED]@ucar.edu>
Cc: Michael Richards [REDACTED]@ntsb.gov>
Subject: RE: Radar interpretation of crash

Scott, this is great. Thank you! I have two quick questions, and I admit I ask these without yet having fully read the article, so maybe the answers are in there.

- The algorithm is only speaking to areas where we have reflectivity, correct? It is not making any sort of assessment in the "white" areas of the plot, which are masked out, right?

That is correct, the results are only valid within the radar echo.

- I am struggling a bit with what the 0-1 interest values mean practically. Would a proper way to describe this in plain language be something like confidence that the particular queried environment (i.e., mixed phase, small drops or freezing drizzle) exists, but exclusive to either of the other two environments? In other words, the red in the plot below say that there is a 100% confidence a mixed phase environment exists based exclusively on the radar data, but says nothing about whether freezing rain or small drops also exist there?

You are not alone on this! I think that confidence is a pretty good way to think of it. I actually prefer to think of it as a measure of how consistent the measurements are with the category. So an output of 1.0 means that every indicator that goes into the algorithm is within the expected values for mixed phase. It is important to keep in mind that the radar data alone won't be conclusive, but in this case it indicates that there is a pretty strong signature of mixed phase. The RadIA results combined with the vertical gradients and my own assessment, I am comfortable saying that mixed phase is pretty strongly indicated by the radar.

I wish it could be a yes or no answer.
Hope this helps, let me know if you have further questions.
Scott

Mike

From: Scott Ellis [REDACTED]@ucar.edu>

Sent: Wednesday, June 26, 2024 11:23 AM

To: Michael Richards [REDACTED]@ntsb.gov>; Alex Rugg Stebbins [REDACTED]@ucar.edu>

Subject: Re: Radar interpretation of crash

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Hi Mike,

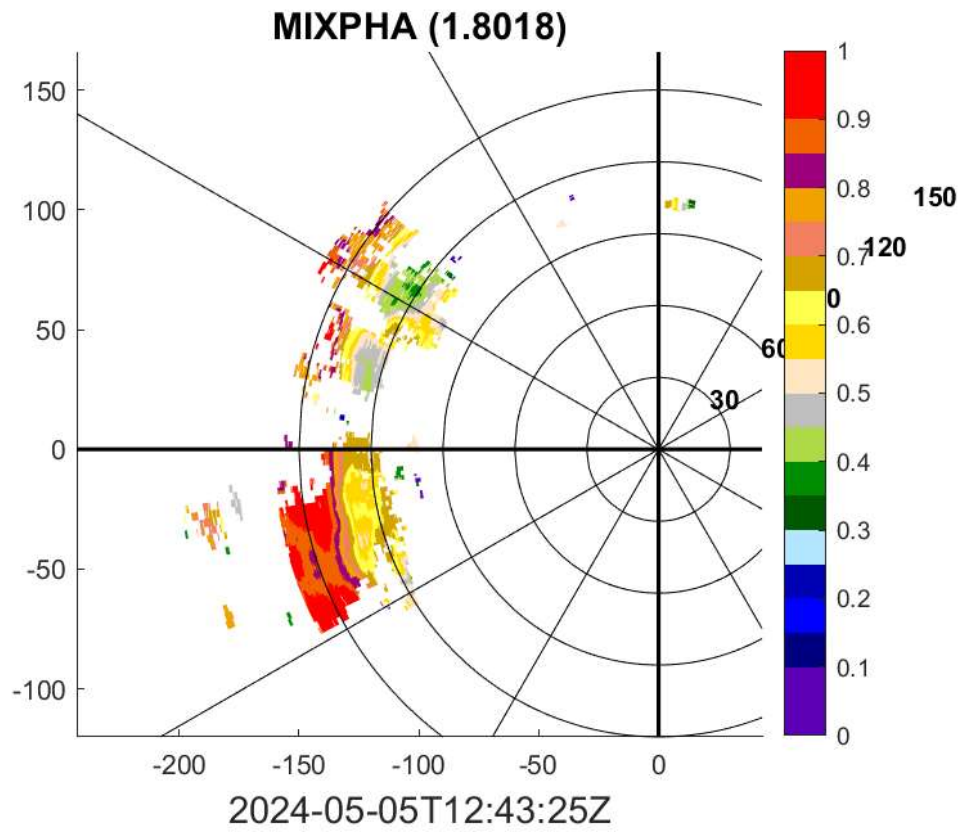
Thanks for confirming the elevation angle, this is the one I was also looking at. The RadIA algorithm is actually separate fuzzy logic algorithms tuned to identify different icing conditions. There are freezing drizzle, small drop and mixed phase algorithms. The freezing drizzle and small drop algorithms don't show any indication that the radar signature is consistent with those conditions. The Mixed phase algorithm shows that the radar measurements are consistent with mixed phase icing conditions to varying degrees, which is in line with my examination of the data and with the Kumjian et al 'fingerprint' of riming. Attached is a plot of the output from the RadIA Mixed phase algorithm for the 1.8 deg KAKQ data. I did not save the freezing drizzle and small drop output because they did not have any indication of those conditions, but I can if needed.

It is important to keep in mind that the 0 to 1.0 output of the RadIA algorithms are not strictly probabilities, they are measures of whether or not the measurements are indicative of the given icing conditions. For example the final output of the different fuzzy logic outputs could sum to more than 1.0 due to overlap in the radar signature of different species of hydrometeor.

Also attached is the Serke et al reference that describes the algorithm.

Let me know if you have any questions. I am available to meet again if that would be easiest.

Cheers,



Radar Icing Algorithm: Algorithm Description and Comparison with Aircraft Observations

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ABSTRACT: Detection of in-flight icing hazard is a priority of the aviation safety community. The “Radar Icing Algorithm” (RadIA) has been developed to indicate the presence, phase, and relative size of supercooled drops. This paper provides an evaluation of RadIA via comparison to in situ microphysical measurements collected with a research aircraft during the 2017 “Seeded and Natural Orographic Wintertime clouds: the Idaho Experiment” (SNOWIE) field campaign. RadIA uses level-2 dual-polarization radar moments from operational National Weather Service WSR-88D and a numerical weather prediction model temperature profile as inputs. Moment membership functions are defined based on the results of previous studies, and fuzzy logic is used to combine the output of these functions to create a 0 to 1 interest for detecting small-drop, large-drop, and mixed-phase icing. Data from the two-dimensional stereo (2D-S) particle probe on board the University of Wyoming King Air aircraft were categorized as either liquid or solid phase water with a shape classification algorithm and binned by size. RadIA interest values from 17 cases were matched to statistical measures of the solid/liquid particle size distributions (such as maximum particle diameter) and values of LWC from research aircraft flights. Receiver operating characteristic area under the curve (AUC) values for RadIA algorithms were 0.75 for large-drop, 0.73 for small-drop, and 0.83 for mixed-phase cases. RadIA is proven to be a valuable new capability for detecting the presence of in-flight icing hazards from ground-based precipitation radar.

KEYWORDS: Icing; Aircraft observations; Radars/Radar observations

1. Introduction

In-flight icing (IFI) of an aircraft is caused by accretion of supercooled liquid water (SLW) to an airframe, which results in the reduction of airspeed and lift, and additional drag and mass. These factors can often lead to a loss of control. The detection and avoidance of IFI conditions is crucial to aviation safety (Landsberg et al. 2008), and is therefore a primary objective of the Federal Aviation Administration’s (FAA) Aviation Weather Research Program (AWRP). Regulations (FAA Advisory Circular, 2014/15) have been put in place so that new aircraft can respond in an appropriate manner to the presence of supercooled small-drop liquid water (SSLW; defined as maximum drop diameter $D_{\max}$ up to 100 μm) and supercooled large drops (SLD; defined as $D_{\max}$ greater than or equal to 100 μm). In this work, $D_{\max}$ is defined as the largest size bin where at least 10 particles were counted, roughly equivalent to a concentration in that bin of $>85 \text{ m}^{-3}$, as described in Cober and Isaac (2012). The FAA further divides the SLD category into freezing drizzle (FZDZ; defined as maximum drop diameter from 100 to 500 μm) and freezing rain (FZRA; defined as maximum drop diameter above 500 μm). Both SSLW and SLD represent significant and different IFI hazards to aircraft. SSLW contributes mainly to ice riming along leading edges and is more likely to be addressable by protective measures such as mechanical boots, or leading-edge heating. SLD is potentially more dangerous in that the larger drops can impact and roll or splash beyond any

protective measures positioned near the leading edges (Brahimi et al. 1997).

To that end, the National Center for Atmospheric Research (NCAR) has been working to develop tools to accurately detect and warn on the presence of these hazard categories. One approach was the development of the “Current Icing Product” algorithm, which combined data from satellite, two-dimensional single polarization weather radar, lightning networks, surface weather observations, and pilot reports with numerical model output to create an hourly three-dimensional diagnosis of the potential for IFI and SLD (Bernstein et al. 2005).

The purpose of this study is to explore the potential for utilizing a dual-polarization radar-based method to infer the presence or absence of several categories of SLW in operational WSR-88D S-band weather radar returns. To do so, the authors explore the potential to detect homogeneous small and large drop SLW (as defined by FAA regulations for appendixes C and O, respectively), and SLW in mixed-phase conditions. Although previous research has identified differing radar characteristics for the FZDZ and FZRA SLD categories (discussed in section 2b), the current study focuses only on FZDZ. The combination of these detection methods is referred to as the Radar Icing Algorithm (RadIA).

Section 2 provides a survey of relevant background information on dual-polarization moments available from the national network of weather radars, a summary of dual-polarization studies during the cold season, and a description of hydrometeor classification algorithms that have been derived from these studies. The RadIA technique is described in section 3,

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including a discussion on its abilities and shortcomings. The algorithm description will include an account of the information extracted from each dataset RadIA employs, the development and application of fuzzy logic membership functions, and how the resulting interest data are interpreted to diagnose the presence/absence of in-flight icing. Section 4 begins with an overview of the “Seeded and Natural Orographic Wintertime clouds: the Idaho Experiment” (SNOWIE) field campaign, whose research flight data were used to evaluate RadIA interest output. Area under the curve (AUC) analyses are presented for each RadIA algorithm versus research flight data taken from 14 flights. Several individual case studies are analyzed, with a discussion on the collocated RadIA interest output values.

2. Background

a. NEXRAD network and dual-polarization moments

The national network of S-band Doppler radars, known as “Next Generation Weather Radars” (NEXRADs, or WSR-88Ds), were designed to detect the presence of precipitation-sized particles, such as snow, rain, and hail. These radars were designed to transmit and receive horizontally polarized radiation signals. At the same time, research radars (Brunkow et al. 2000; Keeler et al. 2000; Ryzhkov et al. 2005a) were developed and tested that transmitted and received both horizontal and vertical polarized signals, known as dual-polarization radars. Dual-polarization radars provide additional information as to the mean particle shape, size, phase (liquid or solid), bulk density, and preferred particle orientation in each sampled volume. By early 2013, the National Weather Service completed software and hardware upgrades to its network of 159 NEXRADs to collect dual-polarization variables (or radar moments). The dual-polarization NEXRADs measure differential reflectivity (ZDR), correlation coefficient (ρ_{HV}), and specific differential phase (Φ_{DP}), in addition to the equivalent reflectivity (Z_e), Doppler radial velocity (V_r), and spectrum width (W) moments afforded by single-polarization capability. The Z_e field is commonly converted to logarithmic scale and referred to as reflectivity (DBZ). In depth descriptions of the dual-polarization variables and their measurement are provided in the book by Bringi and Chandrasekar (2001), but a brief discussion follows.

ZDR is the ratio of horizontal copolar received power to the vertical copolar return, expressed in dB. Copolar refers to transmitting and receiving the same polarization signal. One way to interpret this field is a power-weighted mean axis ratio of the particles in the volume. Cloud drops are small and nearly spherical so tend to have ZDR values near 0 dB and small Z_e values. Larger precipitation-sized drops become somewhat oblate as they fall and thus have ZDR values between +0.3 and +2.0 dB. Pristine ice crystals typically fall with their major axis aligned horizontally and thus also have ZDR values that are positive.

ρ_{HV} is the correlation between horizontal and vertical copolar signals within the radar dwell time. Solid particles coated with liquid water or with extremities that are recently melted,

tumbling solid particles, and mixed phase conditions result in decorrelation in polarizations so that ρ_{HV} values are typically below 0.92. Ground clutter and biological targets have maximums in normalized density distributions starting at 0.80 and below (Radhakrishna et al. 2019). Homogeneous rain or ice result in ρ_{HV} values above 0.95.

Φ_{DP} ($^{\circ}$) is a measurement of differential propagation phase. The specific differential phase K_{DP} is estimated as the range derivative of Φ_{DP} along each radar beam and is expressed in $^{\circ} \text{ km}^{-1}$. Positive K_{DP} values occur when the beam travels through oblate liquid water drops of any temperature. Positive K_{DP} values are also commonly observed in melting ice (e.g., melting snow or graupel) and in horizontally aligned pristine ice crystals such as needles, columns, or plates and dendrites.

b. Cold season studies using dual polarization

SLW is predominantly a cold season phenomenon, with the noted exception of its existence within convective updrafts that tend to occur in the warm season. Previous weather radar studies have documented the general characteristics of winter storms (Stewart et al. 1984, 1990; Stewart 1992). Using a small number of research radars with dual-polarization capabilities (Doviak and Zrnić 1993; Zrnić and Ryzhkov 1999; Bringi and Chandrasekar 2001), various research groups began publishing their findings on how dual-polarization data could be used to remotely detect the general characteristics of winter storms (Kennedy and Rutledge 2011; Andrić et al. 2013) and, more specifically, the existence of varying microphysical conditions within the radar volume. For example, water phase detection was detailed with studies on rain versus snow discrimination (Ryzhkov and Zrnić 1998) or freezing-level detection (Fabry and Szyrmer 1999; Brandes and Ikeda 2004; Ikeda et al. 2005; Giangrande et al. 2008; Boodoo et al. 2010). The characteristics of freezing rain were observed by Zerr (1997) and associations between the observed polarimetric variables were suggested by Van Den Broeke et al. (2016).

Other solid-phase particle types that rely on the presence of SLW are ice pellets and graupel. Ice pellets form when SLW of drizzle size or larger freeze, or when solid particles fall through an intervening above freezing layer then refreeze in a subfreezing layer closer to the surface. Ice pellets observations at the surface during several winter storms were documented by Gibson and Stewart (2007) and Gibson et al. (2009), and Kumjian et al. (2013) described associations between observed polarimetric variables during the refreezing of large supercooled drops.

Graupel forms when solid phase particles fall into a layer with SLW and depositionally accrete the SLW. The formation of graupel (described in Reinking 1975) was examined in observational studies (Takahashi and Fukuta 1988) and Hogan et al. (2002) described associations between observed polarimetric variables and graupel.

c. Hydrometeor classification algorithms

Hydrometeor classification algorithms (HCAs) from weather radar moments refer to a family of algorithms that

retrieve information on the dominant hydrometeor type within a given sample volume. Earlier methods used dual-polarization radar moments in a fuzzy logic classifier (Vivekanandan et al. 1999; Straka et al. 2000; Ryzhkov et al. 2005b) and another version used a neural network/fuzzy logic classifier (Liu and Chandrasekar 2000). The Park et al. (2009) HCA used fuzzy logic along with estimates of confidence based on possible error sources and matrix weighting of input variables. The Vivekanandan et al. (1999) algorithm was based on fuzzy logic membership functions using Z_e , K_{DP} , ρ_{HV} , and ZDR, along with a temperature profile from an available atmospheric sounding or numerical weather prediction (NWP) model output to evaluate the most likely dominant hydrometeor type present at every range gate within a beam and along every tilt within a scan volume. The researchers found that the polarimetric membership functions for supercooled liquid water completely overlapped with irregular-shaped ice (i.e., ice that is characterized by zero average ZDR and zero average K_{DP}).

It has been noted in several research studies (Vivekanandan et al. 1999; Lakshmanan et al. 2010) that all HCAs have relatively poor performance in winter storms when attempting to discriminate SLW from ice. A statistical comparison of some of these HCAs found that they worked relatively poorly for winter season scenarios (Elmore 2011). Thus, even with these dual-polarization moments' ability to identify hydrometeor shapes, ambiguity remains. Later work focused on defining the quantitative benefit of basing an HCA first on an NWP model thermodynamic profile (Schuur et al. 2012) to deduce crystals, dry snow, wet snow, ice pellets/sleet, rain, freezing rain, and a mix of freezing rain and ice pellets. Recently, an unsupervised data-driven clustering technique (Grazioli et al. 2015) was proposed and compared to two-dimensional video disdrometer imagery that could potentially differentiate rain, melting snow, ice aggregates, and rimed ice.

Previous work (Bader et al. 1987; Raga et al. 1991; Wolde and Vali 2001; Field et al. 2004) attempted to validate various versions of HCA through comparison to research flight data. During SNOWIE, two instrumented research aircraft each encountered significant supercooled liquid water, many cases which included large drops of mean diameter greater than 100 μm . Preliminary results for the detection of large drop IFI icing (Serke et al. 2017) were presented for a single case over the terrain north of Boise, Idaho.

While the field of HCA development has been progressing, none have focused specifically on the various conditions that lead to the threat of IFI during the cold season and none can specifically address the needs of the FAA appendixes C and O regulations. The development of a RadIA, (described in section 3), which uses an NWP model temperature profile and real-time operational dual-polarization radar moments, is meant to address these regulatory needs.

3. The "Radar Icing Algorithm" technique

The input radar data for RadIA (Fig. 1) are assumed to have been processed with an algorithm such as Clutter

Mitigation Decision (CMD; Hubbert et al. 2009a,b) and a clutter filter such as Gaussian Model Adaptive Processing (GMAP; Siggia and Passarelli 2004), which are used by NEXRAD Open Radar Products Generator (ORPG). The radar moments are first used within a melting/freezing-level detection module (section 3a), and the resulting melting-level height along with a single input model temperature profile per radar are then ingested into a model temperature profile adjustment module (section 3b). This step is followed by the HCA module (section 3c), which identifies the subfreezing meteorological targets that will serve as inputs to a fuzzy logic module. Next, dual-polarization moment membership functions are generated for each microphysical category from the findings of previous field campaigns and applied to the moment data to generate nondimensional interest values (0–1) for the presence of SSLW, SLD, and mixed-phase conditions (subsections of section 3d). These three algorithms were chosen for inclusion in RadIA because

- 1) they addressed specific FAA IFI regulations (i.e., appendixes C and O) and/or
- 2) they were each the focus of specific radar-based research flight campaign studies that were deemed to be able to detect IFI-related microphysical conditions.

The design of the fuzzy logic algorithms was based on principles of cloud physics as they have been observed and reported on from various field campaigns where instrumented research aircraft were flown. RadIA was developed, applied, and validated (Serke et al. 2011) using Colorado State University's highly calibrated CHILL research radar (Junyent et al. 2015). This work details the first application of the RadIA to the operational NEXRADs.

a. Application of melting-/freezing-level detection

When hydrometeors transition from frozen or solid particles to a liquid state, vertical profiles of radar variables typically display distinct features. Using these features, a Freezing Level Detection Algorithm (FZLA) was designed that uses plan position indicator (PPI) radar data, in which the radar scans in azimuth at a constant elevation angle relative to local horizontal. When viewing PPI scans of radar data, the freezing level is typically seen as a "ring" of values that are substantially different from the values nearer or farther (equivalent to above or below the FZLA altitude, since each radar scan is at a given tilt angle) than the freezing-level range. The FZLA algorithm identifies these rings on a PPI-to-PPI basis, and estimates a freezing level as a height relative to the radar based on the given tilt angle and some trigonometry.

The human eye can easily see a ring of distinctly low values of the ρ_{HV} in the PPI image shown in Fig. 2. This ring marks the freezing level and often occur at a constant height above the radar, at least for typical stratiform-type precipitation. An exception to this statement occurs when horizontal temperature gradients across the radar domain become significant, such as in the presence of synoptic fronts, resulting in sloping melting levels. These situations are not yet accounted for within the freezing-level algorithm. The ring filter algorithm

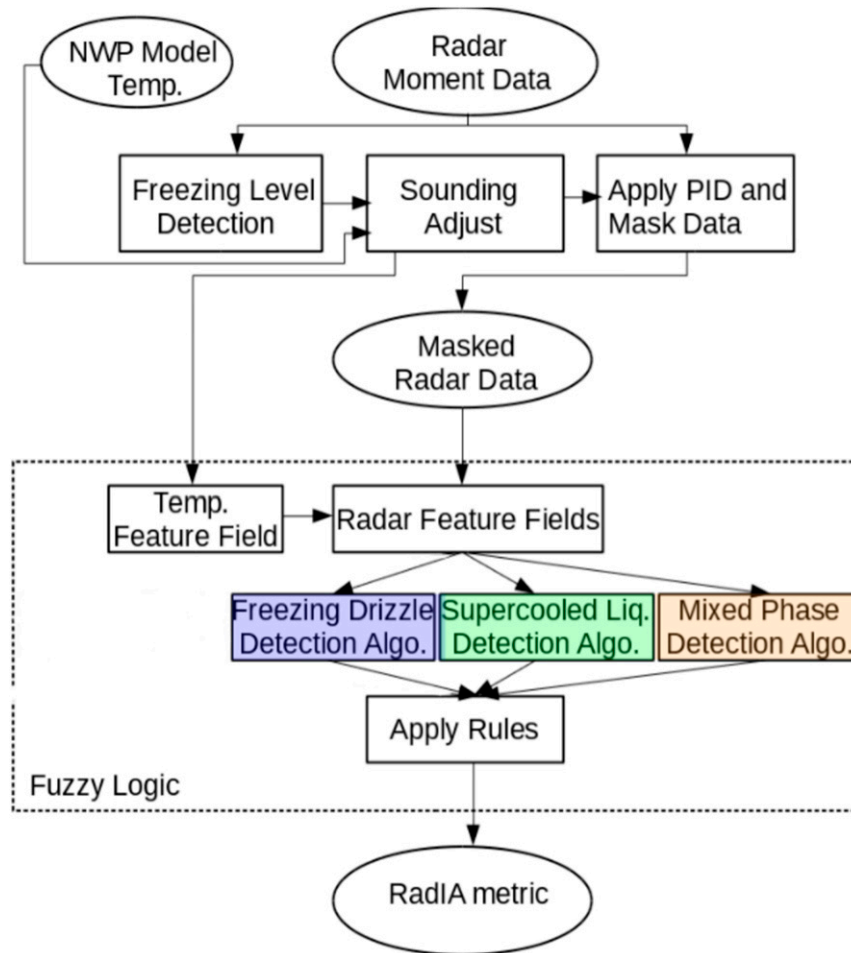


FIG. 1. Flowchart of RadIA. Green-shaded features are not used in the current RadIA, but the architecture allows for these in future versions.

attempts to identify the ringlike pattern in the same way that the human eye does. This is done using a moving two-dimensional spatial template that defines a set of points over which to perform a calculation. The set of points is defined by the template, and it changes based on the center point of the template. The template consists of three regions: center, inner, and outer. The data values in each of these regions are used to compute a “ring interest” in the range 0 to 1 with 1 being ringlike and 0 being not at all ringlike. The diagram in Fig. 3 shows an example of the ring template centered at a particular point (r, a) , with r denoting range, and a denoting azimuth. The mean moment value difference between the center (green) region and the noncenter (blue and red) regions are computed, and a derived ring interest value $[\text{Ring}(r, a)]$ is computed for that point. For the ρ_{HV} image in Fig. 2, the ring filter yields the interest images shown in Fig. 4. The template that was used is shown at top right of center (pink and brown curved bars). The ring of low ρ_{HV} due to melting snow seen in Fig. 2 can be seen in Fig. 4 as high interest values. Some other areas manifest locally elevated interest

even though they are not part of the ring associated with the melting layer.

The same approach was also applied to the reflectivity and ZDR fields, which typically show the ringlike patterns in the presence of a melting layer. Only the templates and parameters change. The ring finding results of the reflectivity, ZDR, and ρ_{HV} are merged by selecting the maximum height of the maximum $\text{Ring}(r, a)$ value at each grid point. A threshold value was applied, and each resulting contiguous ring feature was evaluated for quality. Ring quality was defined as a fuzzy function based on size, shape, and qualitative value attributes. The current example is shown in Fig. 5, with each ring feature color-coded with its derived quality value. Two noncontiguous shapes with quality values above 0.60, and a small ring shape with quality near 0.50 are seen. Note that both ring segments are at a similar range from the radar and correspond to the detected freezing level. Finally, the mean height at the center range of the ring shape is used to compute the height of the freezing layer for the given radar volume. More details and examples of the FZLA can be found in Albo et al. (2010).

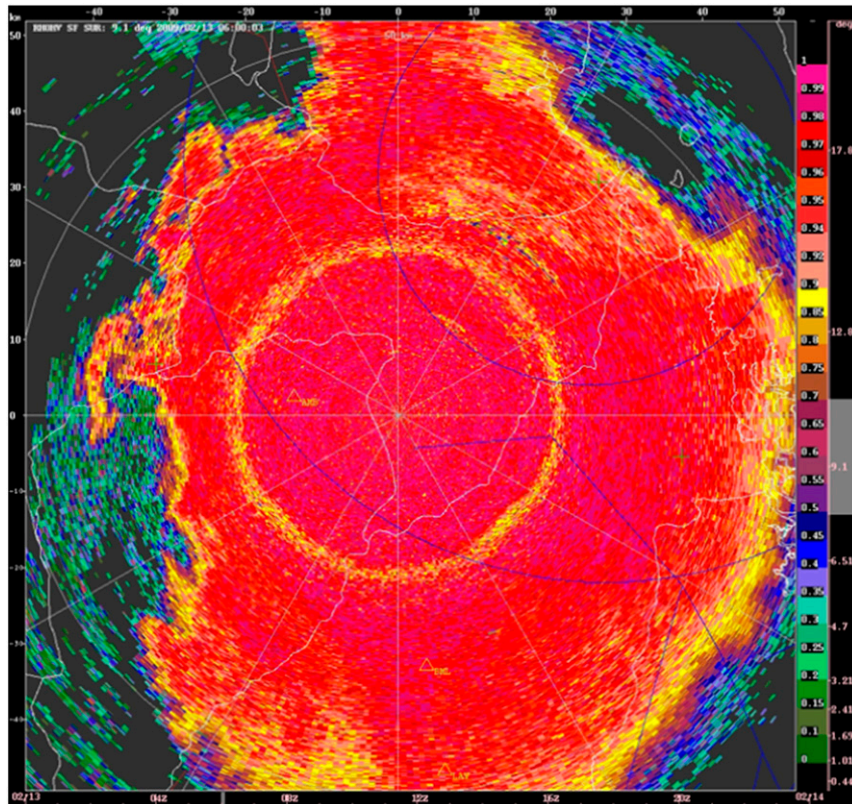


FIG. 2. PPI ρ_{HV} data from the CP2 S-band 10.7-cm wavelength radar located in Brisbane, Australia, operated by the Centre for Australian Weather and Climate Research at an elevation angle of 9.1° .

Temperature profiles from the Weather Research and Forecasting Rapid Refresh (WRF-RR; version 3) 2-h forecast were used in RadIA algorithm development, but temperature profiles from any current or future model could be used. The ORPG currently ingests temperature and relative humidity profiles from the WRF-RR model that runs operationally at the National Centers for Environmental Prediction.

The FZLA algorithm is known to be robust and has been proven to accurately detect the freezing height in stratiform radar return conditions (Brandes and Ikeda 2004). Known weaknesses in the detection of melting-layer height include nearly isothermal conditions with height near the freezing point, detection of a lower-level refreezing level in cases of freezing rain, and in cases with only partial return rings in the PPI or noncontinuous return areas.

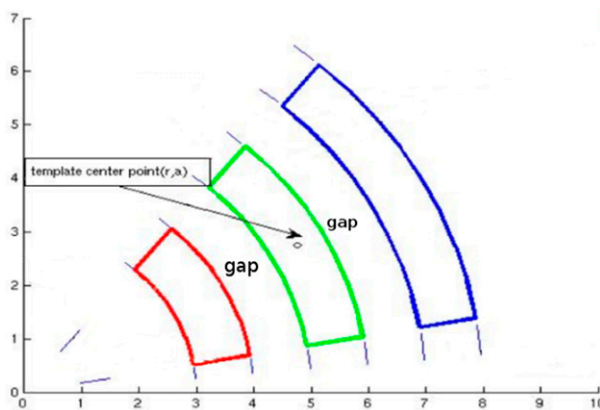


FIG. 3. A diagram illustrating the ring filter used to detect the freezing level.

b. Application of model sounding adjustment

The FZLA height value is then compared to the temperature at the same height in the NWP model profile. The temperature difference between these two is then applied to every NWP model temperature value in the profile. If no radar-based freezing level has been detected by the FZLA, the NWP model profile is left unchanged. This temperature profile that has been adjusted based on radar-derived height of the freezing level is then passed to the HCA module.

WRF-RR, version 3, vertical temperature root-mean-square errors were found to be on the order of 1 K (Benjamin et al. 2016). Random errors of this magnitude should not have a significant effect on derivation of freezing-level heights. Spatial differences between actual and forecasted precipitating clouds could lead to more significant errors.

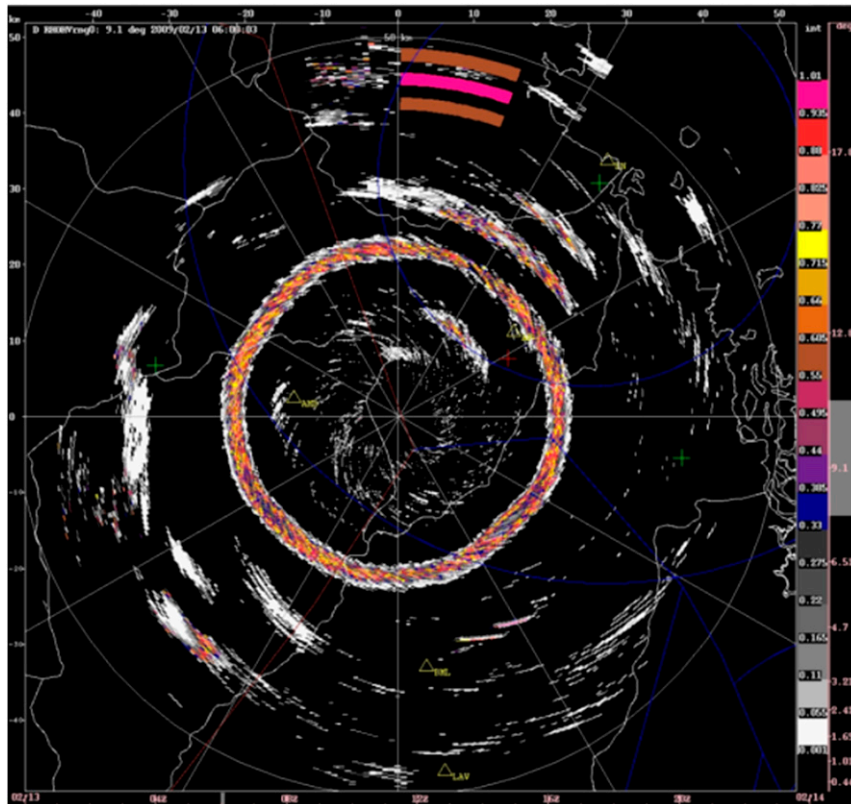


FIG. 4. PPI ρ_{HV} data from Fig. 2 that have been processed by the ring filter illustrated in Fig. 3.

c. Application of the classic hydrometeor classification algorithm

RadIA utilizes HCA (Vivekanandan et al. 1999) only to mask out return associated with warm rain (existing at temperatures warmer than 0°C), clutter, and biological targets from further processing. The RadIA algorithms described in the next section (section 3d) are then used to differentiate the various IFI categories using only areas that have passed through the HCA masking step.

d. Application of RadIA fuzzy logic algorithms

RadIA consists of three different fuzzy logic inference modules, or algorithms, that are designed to identify distinct icing conditions, including SSLW, SLD, and mixed phase (MIXPHA). The RadIA technique utilizes fuzzy membership functions to develop nondimensional interest values for use in the algorithms. The use of multiple membership functions within each IFI detection algorithm can effectively account for uncertainties in the range of each individual fuzzy logic feature field value used, while mimicking the gradual transition from icing to nonicing environments associated with each moment value. The design of the fuzzy logic algorithms was based on principles of cloud physics as they have been learned and reported from various observational field campaigns where instrumented research aircraft have flown. The following list describes the general processing steps for each of the

three RadIA algorithms (SSLW, SLD, and MIXPHA) that are involved in determining the presence or absence of a given category of microphysical classification:

- 1) Define the membership functions (discussed for each individual algorithm in the following subsections). The functions are used to determine the likelihood that a given return feature is a positive (negative) indication for the presence (absence) of each in-flight icing category.
- 2) Calculate spatial statistics of moments (i.e., mean, standard deviation, and texture of local area moments; the calculation of these are described in the next subsections).
- 3) Interpolate the spatial statistics of moment values through the membership functions to create “feature fields.” Note that the feature fields are single values for each range gate calculated over a specified domain.
- 4) Combine feature fields into an interest value (0–1 continuous scale).
- 5) Using receiver operating characteristic (ROC)-AUC analyses, determine and apply thresholds to the interests (discussed in section 4b).

In the following subsections, the authors describe the research studies upon which the three RadIA algorithms are based and the resulting membership functions that comprise each algorithm.

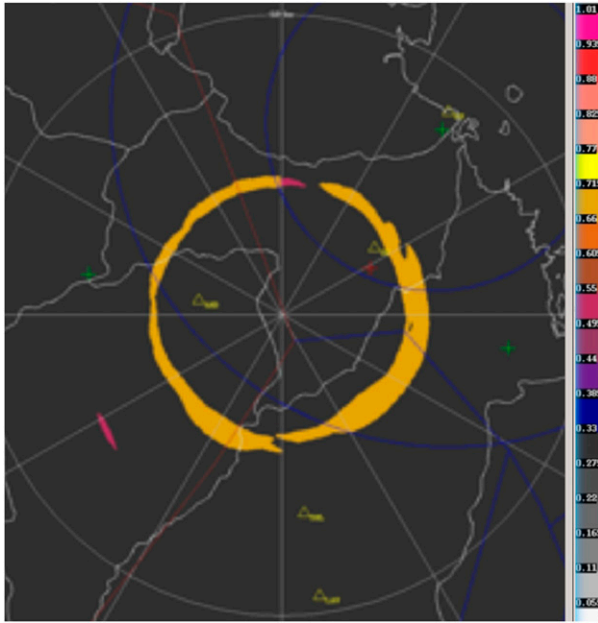


FIG. 5. PPI data quality ring feature generated from a combination of the double ring-filtered ρ_{HV} , reflectivity, and ZDR data from 9.1° elevation. The color scale indicates the “quality” or “strength” of the ring feature.

1) SSLW ALGORITHM

As mentioned in the opening paragraph, homogeneous SLW can be subdivided, according to FAA regulations, into small-drop (SSLW, FAA appendix C) and large-drop (SLD, FAA appendix O) categories. SSLW drops are quite small (diameter $< 50 \mu\text{m}$) and have correspondingly low reflectivity values. If the drops are mixed with a small number concentration of larger diameter ice crystals, the ice particles dominate the backscattered radar signatures due to the diameter-to-the-sixth-power relationship in the radar equation. Additionally, small irregular, randomly oriented ice crystals and small liquid drops are both characterized by ZDR and K_{DP} near zero. Thus, discrimination of SSLW and ice crystals with radar alone is challenging.

Plummer et al. (2010), however, showed that discriminating ice from SSLW is possible by comparing airborne particle probe observations with data from the NCAR S-band dual-polarization radar (S-Pol) from the Mesoscale Alpine Program (MAP) field campaign in northern Italy (Bougeault et al. 2001). Plummer et al. (2010) examined histograms of ZDR and K_{DP} and concluded that

- 1) the mean values of K_{DP} and ZDR were greater in regions of ice only as compared to mixed phase (supercooled liquid and ice particles) and
- 2) spatial variance of ZDR and K_{DP} were also greater in regions of ice only as compared to mixed phase.

Plummer et al. (2010) ensemble research aircraft flight data were adapted to form the membership functions of the SSLW algorithm (Fig. 6). The feature fields used in SSLW are

computed over a local area and include the mean of ZDR, standard deviation of ZDR, mean of K_{DP} , and the standard deviation of K_{DP} . The study found no statistically significant value in DBZ or ρ_{HV} to differentiate SSLW from ice-only conditions.

2) SLD ALGORITHM

Ikeda et al. (2009) developed a freezing drizzle detection algorithm for the single polarization NEXRADs that was based, in large part, on local area mean, standard deviation, and texture of reflectivity. They found that radar return within the lowest elevation angle that also produced drizzle at the surface exhibited smoother reflectivity textures than those producing snow. The authors found that they were able to discriminate between these two particle classes at least for 70% of their observed drizzle cases. In the paper presented here, the SLD algorithm refers entirely to the detection of freezing drizzle. Freezing rain detection was not attempted.

The feature fields calculated are 1) the median reflectivity, 2) the standard deviation of the reflectivity, 3) the median of the standard deviation of the reflectivity, 4) the mean squared difference in the reflectivity at each range gate within a small area [texture, as defined in Ikeda et al. (2009, section 2b)], and 5) the median of the reflectivity of the texture. Note that the feature fields are single values for each range gate calculated over a specified domain. In addition, the SLD algorithm uses two domains: the “local” domain (radius = 15 km) and the “global” (radius = 100 km). Consequently, 10 measures were used to calculate 10 scores, which are then combined to determine the final overall score.

As the original SLD algorithm was designed to identify freezing drizzle at the surface, modifications were required to extend the identification of large drop IFI at radar tilt elevations higher than the lowest single tilt to be applicable for aircraft icing detection within RadIA. RadIA’s SLD is similar to the original SLD but with the following modifications:

- 1) The feature fields of the near domain computed over 15-km range were computed over successive 15-km rings extending in range from the radar and using scans of multiple elevation angles. This extended the freezing drizzle classification above the surface to altitudes useful for aircraft icing detection. The algorithm relies on standard deviations on an elevated surface which intersects an increasing depth of atmosphere with higher tilt angle. Quantifying the effect of utilizing higher tilt angle radar data on algorithm accuracy as not yet been addressed and is reserved for future analyses.
- 2) In the original SLD algorithm, the 100-km domain was used as a proxy for the vertical structure. For RadIA’s SLD, multiple elevation angles are used with the 15-km domain thus obtaining vertical structure information across a smaller horizontal extent. The 100-km domain was therefore not used in RadIA’s SLD.
- 3) A feature field, called “texture of dBZ” (abbreviated to “TDBZ”), was added to SLD. This field is the mean of the gate-to-gate difference of reflectivity in range.

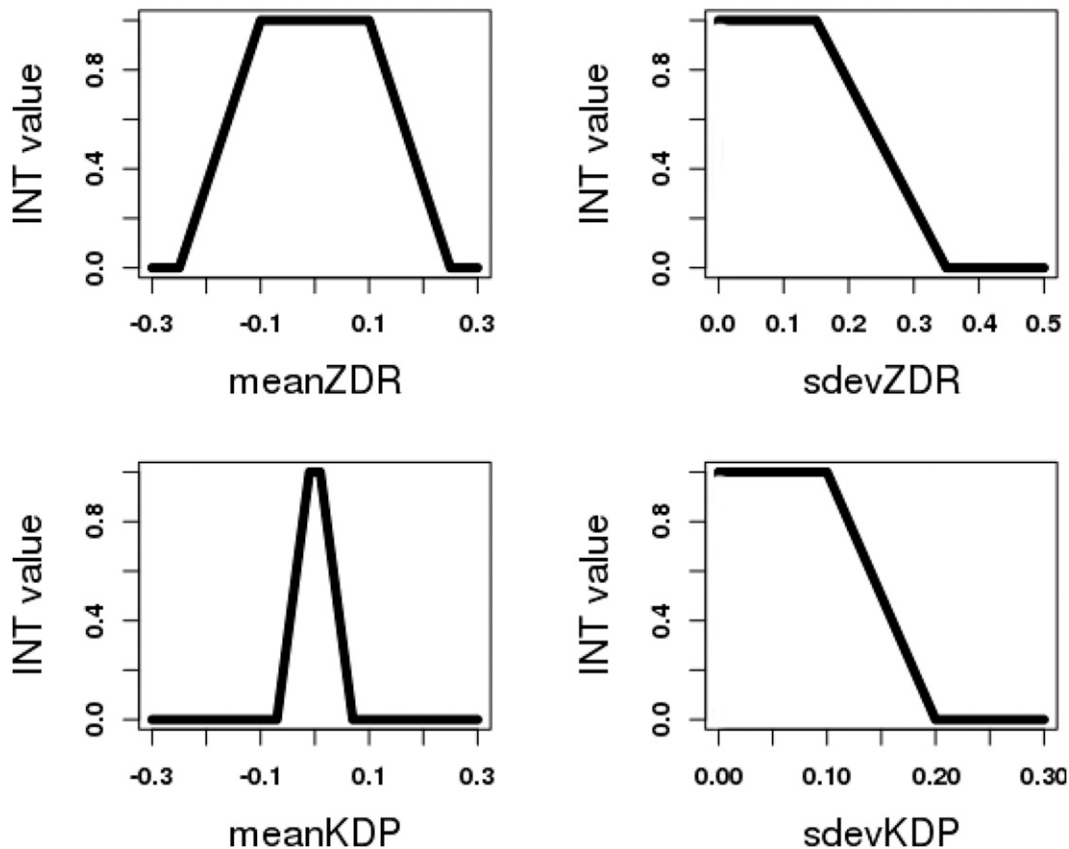


FIG. 6. SSLW algorithm membership functions for (left) mean and (right) standard deviation of (top) ZDR and (bottom) K_{DP} .

- 4) A flag was added after the fuzzy logic module using the mean ZDR. Its purpose is to exclude radar return pixels that are significantly removed from zero (nonspherical particle shapes). If a pixel's mean ZDR was greater than 1.5 dB, the SLD interest was set to zero, no matter what the reflectivity-based interest value was.

The membership functions for the RadIA's SLD algorithm are shown in Fig. 7 and are based on evaluations of the ensemble research aircraft flight dataset used in the Ikeda et al. (2009) study.

3) MIXED-PHASE ALGORITHM

When liquid and solid hydrometeors exist in the same volume of air at the same time, it is referred to as mixed phase. Trapp et al. (2001) and Field et al. (2004) observed dual-polarization radar attributes in mixed-phase conditions. Williams et al. (2015) suggested an algorithm to detect mixed-phase conditions in a radar volume. They showed that some icing conditions can be detected "indirectly" with polarimetric data by inferring the microphysical processes that produce SLW. The idea is that these microphysical processes may yield precipitation particles with polarimetric signatures that indicate the coexistence of SLW. The study examined ice crystal formation and the associated presence or absence of

SLW under conditions of (i) ice saturation only versus (ii) ice supersaturation and water saturation. Laboratory experiments and in situ measurements from research aircraft show that condition (i) supports pristine ice crystal growth, such as plates and columns, has a very low possibility of containing SLW, and does not pose an aircraft icing hazard. These pristine ice crystals grow via vapor deposition and are usually characterized by low reflectivity values (-10 to 10 dBZ), and very high ZDR values (>5 dB). Under condition (ii), dendrites grow, possibly with associated riming. The dendrites produced in the presence of SLW are typically less anisotropic and less dense (lower fraction of ice to air), but their growth is quite rapid, and the ice particles are typically much larger than the ice particles that form due to condition (i). The authors found that the radar signatures of (ii) are higher reflectivity values than (i), ranging from about 10 to 30 dBZ and ZDR lower than (i), around 1 – 3 dB. The K_{DP} signatures (not used) of (i) and (ii) overlap since K_{DP} is a function of the bulk density of the particles, as well as particle shape and orientation Bailey and Hallet's (2009) crystal habit diagram show dendrite dominance when humidity conditions were above the water saturation boundary and temperature was between -10° and -15°C , so RadIA's MIXPHA algorithm includes an NWP temperature membership function. RadIA's MIXPHA membership functions are shown in Fig. 8.

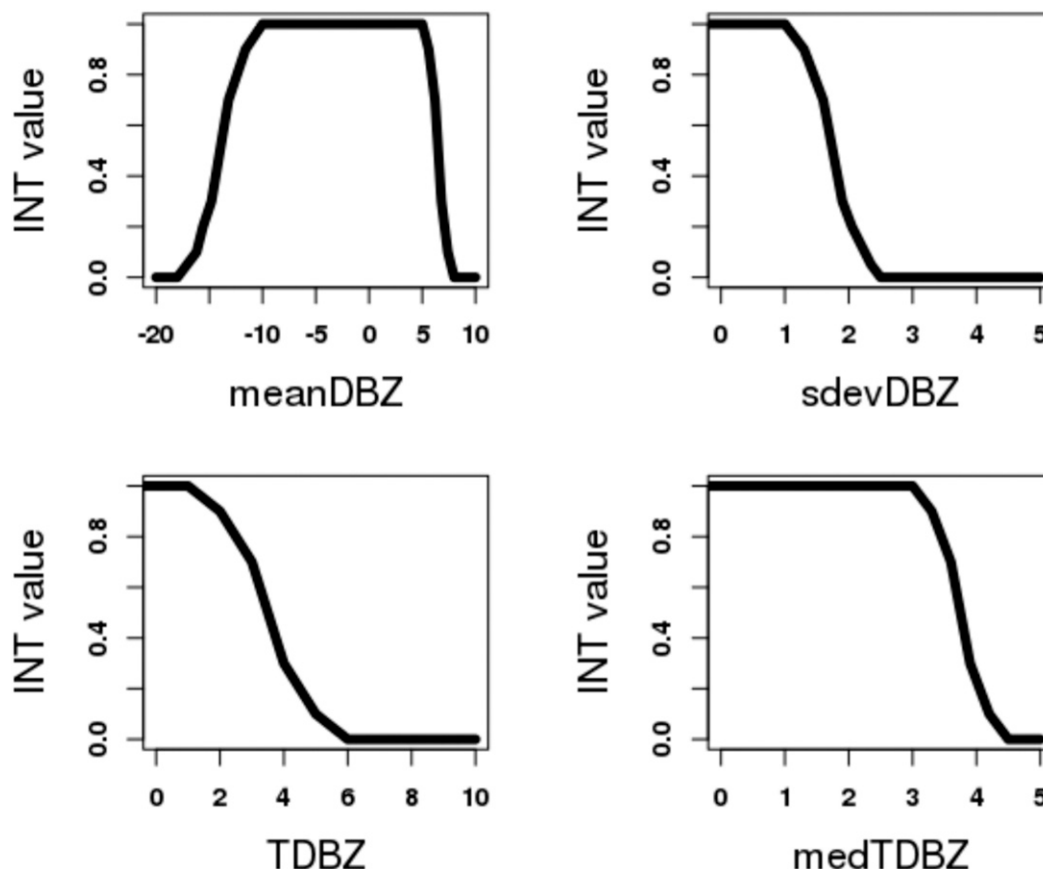


FIG. 7. SLD algorithm membership functions for (top left) meanDBZ, (top right) sdevDBZ, (bottom left) texture of DBZ, and (bottom right) median of the texture of DBZ.

e. The effects of moment biases and signal degradation with range on RadIA output

The quality of the RadIA output, like all algorithms, is dependent on the quality of the input data. Signal-to-noise degrades with range, and this loss of sensitivity leads to a decrease in RadIA's skill with increasing range from the radar. Nonuniform beam filling (NBF; Ryzhkov 2007) is also a significant consideration which decreases RadIA's detection capability. While this is not unique to RadIA, it should be taken into account when interpreting results.

The mean of the WSR-88D ZDR measurements can be biased for several reasons including miscalibration (Williams et al. 2015) and cross-coupling of the horizontal and vertical polarized signals (Hubbert et al. 2010a,b; Wang and Chandrasekar 2006). These biases can be large enough (multiple tenths of a dB) to impact the performance of RadIA. Although the fuzzy logic design results in some robustness to these biases in ZDR by utilizing multiple inputs and avoiding discrete thresholds, the output will be adversely affected by these biases. For example, the SSLW algorithm has as one of its four inputs the mean ZDR and its membership function is fairly narrowly focused around 0 dB. For values of mean ZDR with a magnitude greater than 0.25 dB the membership

function is 0, indicating low probability of SSLW. Therefore, a ZDR bias of a few tenths would result in mean ZDR falsely indicating SSLW or falsely indicating the lack of SSLW. Although the other three inputs will act as a buffer against spurious answers due to biases in ZDR, there will be RadIA errors that result. The MIXPHA algorithm also uses mean ZDR as an input. While MIXPHA only has three inputs making it more susceptible to errors in mean ZDR, this will be offset by the range of mean ZDR values of the membership function being about 4 dB, meaning that it is more robust to biases of a few tenths of a dB.

4. RadIA comparison to SNOWIE aircraft data

a. SNOWIE campaign overview

From January through mid-March of 2017, SNOWIE was conducted over the Payette River basin just north of Boise (Tessendorf et al. 2019). The overall goals of the project were to understand the natural dynamical and microphysical processes by which precipitation forms and evolves within orographic winter storms and to determine the physical processes

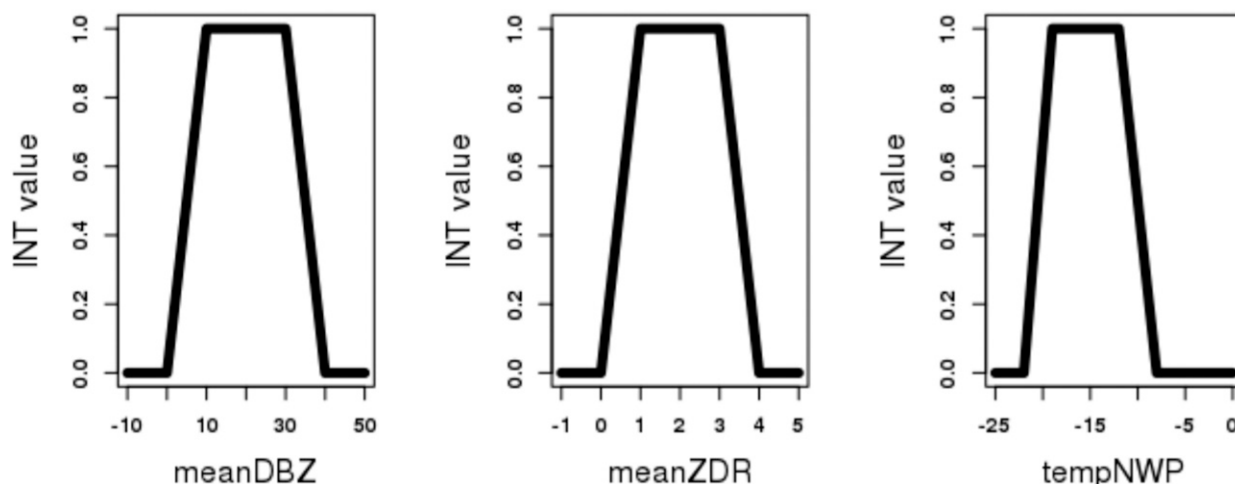


FIG. 8. MIXPHA algorithm membership functions for (left) mean DBZ, (center) mean ZDR, and (right) temperature from the NWP model.

by which cloud seeding works. Successful seeding of clouds relies on understanding cloud/precipitation formation processes and spatial distributions, drop size distribution and quantitative water content associated with SLW. The instrumented University of Wyoming King Air (UWKA) provided in situ “truth” datasets. SNOWIE utilized an impressive array of ground-based and airborne remote and in situ sensors to address the project’s goals, all of which were described in detail in Tessendorf et al. (2019).

b. Aircraft probes utilized

The primary probes utilized in this comparison were the Rosemount Icing Detector (RID; Baumgardner and Rodi 1989), the Nevzorov hotwire probe (Korolev et al. 1998), and the two-dimensional stereo (2D-S) probe (Lawson et al. 2006). Particle imagery from the 2D-S probe were used to derive maximum particle diameters as well as ice-only and liquid-only particle distributions. Details of the 2D-S’s usage are found in the next section. The RID is equally sensitive to all drops between 50 and 500 μm in diameter. The Nevzorov hotwire probe is sensitive to drops with diameter down to 20 μm and its sensitivity rolls off for drops above 100 μm . Differencing of the liquid water contents (LWCs) from these two probes provides a useful proxy to presence of large drops.

c. Methodology

The first requirement was to quality control the aircraft probe datasets. This process involved flagging and removal of bad data periods due to instrument outage or ice-over, accounting for baseline drift, and removal of the heat cycling periods in the RID (French and Majewski 2017). The 2D-S imagery was then processed through Environment and Climate Change Canada’s algorithm (Korolev and Heckman 2019) for shape (and thus phase) classification. The solid and liquid binned size distributions exclude particles < 50 μm in diameter since it is difficult to discern spheroid from

nonspheroid shapes with the number of available 2D-S pixels below this diameter threshold. Thirty-second averages were computed of all the aircraft fields such as location, ambient temperature, probe LWCs, maximum particle diameters, and mass liquid fraction (MLF) field from the SNDI-like algorithm. Averaging was conducted to smooth the high-temporal-resolution probe data, allow for meaningful quantities of particle imagery data to be binned in each liquid and ice distribution period, and to more closely represent the azimuthal resolution of polar coordinate NEXRAD data at the Convair’s typical flight distance from Boise’s KCBX radar. A total of 2643 thirty-second flight segments from the 14 SNOWIE flights were used for this study. The mean time, latitude, longitude, and altitude of each 30-s-averaged segment was then matched to the closest radar sweep in time, as well as range and elevation angle. Due to the fixed flight-track locations during the campaign, the radar tilt that most closely matched the Convair location was always between 2° and 6° elevation. Theoretical calculations by Ryzhkov et al. (2016) found that the change in NEXRAD dual polarization from near 0° to a maximum of 20° elevation was less than the calibration accuracy for returns from oblate spheroids. The RadIA interest (INT) values within five range gates (1.25 km) and five azimuthal beamwidths (6.5 km at 80 km range) were collected and the maximum INT value within this box was considered the “matched” INT value for each algorithm to the aircraft location.

The next step in the analysis process was to define criteria to ascertain the presence of FAA appendix C, O, and mixed phase in-flight icing conditions using data from the UWKA probes (Table 1). FAA appendix C criteria were defined as the maximum particle diameter (D_{max}) derived from the 2D-S as being less than 100 μm , MLF greater than 0.20, Rosemount LWC minus the Nevzorov LWC less than 0.02 g m^{-3} , and Nevzorov LWC greater than 0.02 g m^{-3} . The value of 0.02 g m^{-3} was chosen as the Nevzorov LWC threshold since it was approximately the minimum detectable value for the instrumentation. Appendix O criteria were defined as D_{max} derived

TABLE 1. Aircraft probe criteria to confirm the presence of each given RadIA algorithm.

Algorithm	Criteria			
	$D_{\max}$ (μm)	MLF (unitless)	$\text{LWC}_{\text{Rose-Nev}}$ (g m^{-3})	LWC_{Nev} (g m^{-3})
Large drop	≥ 100	$\text{MLF} > 0.2$	≥ 0.02	> 0.02
Small drop	< 100	$\text{MLF} > 0.2$	< 0.02	> 0.02
Mixed phase	—	$0.2 < \text{MLF} < 0.8$	—	> 0.02

from the 2D-S being greater or equal to $100 \mu\text{m}$, MLF greater than 0.20, Rosemount LWC minus the Nevzorov LWC as being greater than or equal to 0.02 g m^{-3} , and Nevzorov LWC greater than the minimum detectable. Mixed-phase criteria were defined as Nevzorov LWC being greater than the minimum detectable and MLF being greater than 0.20 and less than 0.80.

The 0.20 lower boundary on MLF for all three in-flight icing categories was enforced to exclude flight segments that were dominated by solid precipitation sized particles ($\text{MLF} \sim 0.0$). The assumption here was that radar volumes dominated by solid particles were either nearly void of liquid phase particles or actively being scavenged of any remaining liquid particles (Korolev and Isaac 2003). The application of this lower limit threshold on MLF resulted in homogeneous or nearly homogeneous solid-phase particle populations being excluded from analysis of all three of these in-flight icing states. The 0.80 upper boundary on MLF for the mixed-phase in-flight icing condition was enforced to exclude flight segments that approached the homogeneous liquid condition ($\text{MLF} \sim 1.0$). Application of this upper limit threshold on MLF resulted in homogeneous or nearly homogeneous liquid-phase particle populations being excluded from the mixed-phase analysis.

The other criteria used to differentiate large-drop and small-drop in-flight icing are the $D_{\max}$ threshold and the Rosemount/Nevzorov LWC differencing threshold. The 2D-S $D_{\max}$ threshold of $100 \mu\text{m}$ originates from the definition of appendixes C and O in-flight icing regulations by the FAA. A probe LWC difference of $+0.02 \text{ g m}^{-3}$ was chosen as the threshold as it represents a statistically significant difference between the two 30-s-averaged LWC measures that should capture the minimum detectable rolloff in Nevzorov hotwire probe LWC sensitivity that first occurs near the appendixes C and O transition near $D_{\max}$ of $100 \mu\text{m}$.

The final step in the analysis was to compute ROC-AUC values for each RadIA algorithm over the 14 SNOWIE flights in order to illustrate the diagnostic ability of the binary classifier system as its discrimination threshold is varied. In this case, the classifiers are each of the RadIA INTs, which are continuous from 0 to 1. ROC analysis is related in a direct way to cost/benefit analysis of diagnostic decision making. In this study, the models that were tested were the individual combinations of NEXRAD membership functions that were used to derive RadIA interest values (described in section 3d). These models were tested against “truth” values in the form of aircraft probe data, matched spatially and temporally to the closest RadIA INT values. This technique plots false

positive rate (FPR; on the x axis) against the true positive rate (TPR; on the y axis), where a perfect model would have an FPR of 0 and a TPR of 1. For each threshold value between 0 and 1, FPRs and TPRs were calculated, and a corresponding point is plotted on the ROC diagram. When values have been plotted for all possible threshold values, a curve is traced out. AUC is simply the integrated area under that ROC curve, where a value of 1.00 would indicate perfect separation between the FPR and TPR distributions and would represent a model that was always correct. An AUC value of 0.50 means that the model has no discriminatory ability, and an AUC value of 0.00 would indicate a model that was always wrong.

d. Campaign summary analysis

The ROC-AUC plots representing data from the 14 SNOWIE flights for RadIA’s SSLW, SLD, and MIXPHA INT outputs are shown in Fig. 9. This shows false alarm ratio (FAR) on the x axis and probability of detecting a true positive (POD-Y) on the y axis. In these plots, FAR and POD-Y values at 0.05 interest increments are plotted as open circles from 0 to 1, often with overlapping points. The interest values trace a curved line with the closest to the upper left corner of the plot considered as the optimal threshold value used to differentiate a positive and negative detection by the algorithm. AUC is just the integrated area under this curve, with values closer to 1 indicating higher skill at differentiating true positives from false positives. Overall, the AUC values for the three algorithms are all fairly high (all between 0.73 and 0.84), which means that there is significant and meaningful separation between the underlying FPR and TPR distributions. This indicates the models are all doing reasonably well at detecting the presence of each of the three in-flight icing categories. The number (N) of 30-s averaged flight segments are fairly low ($N = 52, 41$, and 168 , respectively) when compared to the total number of available 30-s-averaged flight periods since a vast majority of SNOWIE cases were dominated by local orography effects. This meant that the aircraft was often flying through occasional localized patches of large or small drop in-flight icing instead of long durations of synoptic-scale stratiform icing conditions. As these N values were 2–8 times larger than minimum numbers required to arrive at an acceptable level of statistical significance (generally thought of as at least $N \sim 20$), the authors were comfortable with this positive interpretation of ROC-AUC values derived from the three RadIA algorithms.

Two additional experiments were conducted with the ROC-AUC analyses for the MIXPHA algorithm. In the first,

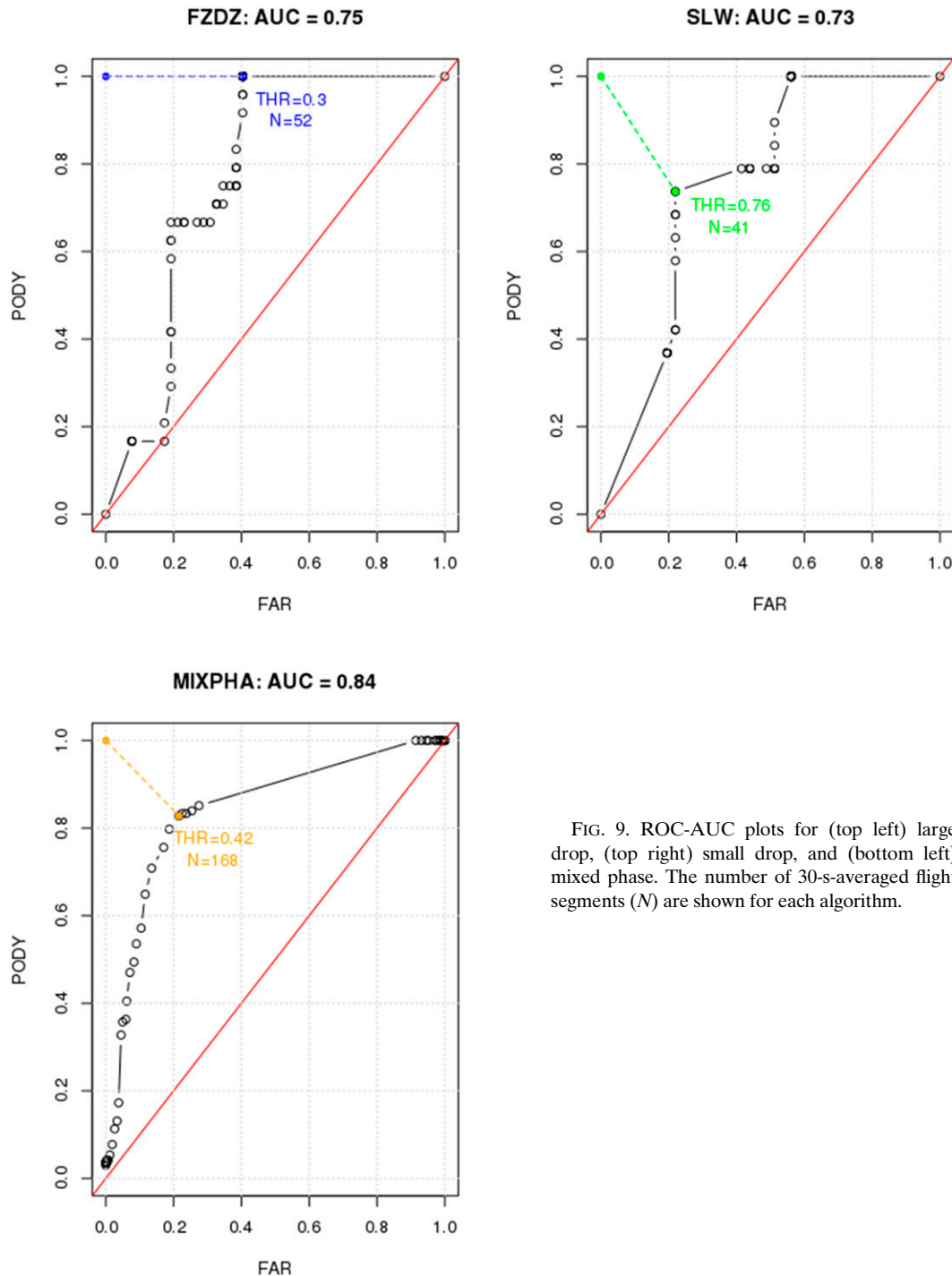


FIG. 9. ROC-AUC plots for (top left) large drop, (top right) small drop, and (bottom left) mixed phase. The number of 30-s-averaged flight segments (N) are shown for each algorithm.

an additional large-drop criterion was added to the standard mixed-phase criteria. In this scenario, the AUC remained high (0.82, $N = 13$) which indicates that the MIXPHA algorithm could work equally well for ice mixed with small or large supercooled drops.

In the second experiment with the MIXPHA algorithm, the minimum LWC threshold was increased from 0.05 ($N = 168$)

to 0.15 ($N = 83$) and again to 0.25 g m^{-3} ($N = 38$). As this threshold was increased, the AUC increased from 0.84 to 0.86 to 0.87, respectively. This result indicates that the MIXPHA algorithm does incrementally better at detecting mixed-phase conditions as the supercooled LWC as measured by in situ probes increases into the range that is more likely to negatively affect aircraft operations.

e. Case study analysis

A case study from 31 January 2017 was chosen to illustrate RadIA's abilities in providing real-time IFI diagnoses. Figure 10 (top panel) shows RadIA SLD interest values from the 2.5° tilt collected at 2022 UTC. The west-to-east flight leg intersects interest values between 0.55 (brown color) and 0.80 (yellow color) at flight level. The Boise NEXRAD (KCBX) reflectivity from the same time and tilt is shown in Fig. 10 (bottom panel). The flight leg intersects reflectivity values from -10 to $+7$ dBZ, which are typical of drizzle.

Figure 11c shows time series of mass ice fraction (MIF; solid gray line, which is 1 MLF), and the RID (open red squares) and Nevzorov LWCs (filled red circles; units: g m^{-3}) from 2016:00 to 2024:30 UTC 31 January 2017. MIF was very low throughout, indicating nearly homogeneous liquid phase conditions. RID LWC was significantly larger than the Nevzorov LWC between 2021:30 and 2023:00 UTC—a clue to the presence of large drops since the RID collection efficiency does not roll off in the presence of drops above $100\text{-}\mu\text{m}$ diameter like the Nevzorov LWC does. Ambient air temperature was between -13° and -15°C (not shown) throughout the period. A time series of RadIA interest values (Fig. 11d) shows SSLW interest near 1.0 throughout the period, as the mean and standard deviation of ZDR and K_{DP} are small. SLD is at or above 0.6 throughout, with values increasing to 0.9 from 2021:00 to 2023:00 UTC. MIXPHA interest values are mostly near 0.50, indicating uncertainty in the presence of this category. This is likely due to the temperature being in the right range, but mean reflectivity and ZDR being too low to have large membership value contributions. Particle size distributions from the 2D-S (filled circles) and CDP (open circles) at 2019:50 UTC (Fig. 11a) and at 2021:30 UTC (Fig. 11b) indicate a significant maximum in concentration of particles in the SSLW size range. At the time shown in Fig. 11a, no particles are observed in the large drop (FAA appendix O) size range. Significant small drop concentrations (FAA appendix C icing) exist, however, as proven by the maximum in CDP near $25\text{ }\mu\text{m}$ (Fig. 11a), the LWC traces (Fig. 11b), and high RadIA SSLW interest value (Fig. 11d). The times of the two particle distributions within the time series plots are indicated with black vertical lines. Figure 11e is a time series of all 2D-S particle images that are greater than or equal to $100\text{ }\mu\text{m}$ in diameter during the period shown in Figs. 11c and 11d. Note that all these particles were recorded between 2020:40 and 2022:00 UTC, indicated by the vertical black arrows. The UWKA instrument operator flight log at 2021:30 UTC noted, “As soon as [the UWKA] started [the flight] leg, need to climb to get out of heavy icing.”

The presence of SLD (FAA appendix O icing) between 2021:00 and 2022:00 UTC was confirmed by the expert instrument operator, the 2D-S distribution (Fig. 11a), increased difference between RID and Nevzorov LWC (Fig. 11b), 2D-S imagery of large round particles (Fig. 11e) and was positively detected by RadIA with SLD algorithm interests near 0.90 (Fig. 11d).

In this SNOWIE case study with SLD and SSLW observed by the Convair particle probes, RadIA's high SLD and SSLW

algorithm interests both accurately detect the presence of homogeneous SLW hazard to aviation.

5. Conclusions

There is an ongoing need in the aviation safety community for detection of IFI conditions with improved spatiotemporal resolution and accuracy. RadIA combines an NWP model temperature profile with dual-polarization moments from operational NEXRAD S-band weather radar to discern the presence or absence of SSLW, SLD, and mixed phase within a radar volume. It relies on dual-polarization based membership functions to detect each of these three IFI conditions. These membership functions were derived based on the findings from several previous research aircraft flight campaigns that operated in airspace that was also being sampled by ground-based dual-polarization radar.

Data from the SNOWIE field campaign were quality controlled, processed through a particle imagery phase/shape classifier, and the relevant aircraft fields were temporally averaged. This work represents 14 research flights and approximately 21 h of flight time. These aircraft data fields were then matched in space and time to the NEXRAD-based RadIA interest outputs. A small volume of RadIA interest locations around the matchup point were deemed as representative of the aircraft location and the maximum interest value for each of the three RadIA algorithms were saved. RadIA's ROC-AUC scores for the aircraft periods that exhibited SSLW, SLD and MIXPHA conditions were 0.73, 0.75, and 0.84, respectively. These values indicate that the TPR and FPR distributions for all three were significantly separated such that the resulting interest values provided a significant amount of skill in detecting the presence/absence of the prescribed IFI conditions.

Based on this analysis, we further conclude that RadIA can provide useful IFI hazard detection when a given NEXRAD is operating within its calibration specifications, when the dual-polarization moment signal-to-noise ratio is significantly above the noise level (approximately within 90 km of a radar for most of these mean particle populations), when the return volume can be viewed by at least one radar beam, when no clutter or other nonweather effects are present in the return, and when particles are large enough to be detected. It is widely known that NEXRADs cannot even detect the presence of very small drops on the order of $20\text{--}30\text{ }\mu\text{m}$. This implies that some homogeneous SSLW cases could be detected by NEXRAD (especially at very close ranges) and some could not. When the converse of these above conditions is true, RadIA output would be expected to either not be available or be inaccurate. As mentioned previously, the SLD output is also expected to be inaccurate at the higher tilt angles due to reliance on standard deviation measures that were meant to represent quasi-horizontally homogeneous conditions in stratiform cold season cloud layers.

The goal of RadIA development is to provide an accurate depiction of IFI conditions using dual-polarization moments to the aviation community to facilitate safer and more

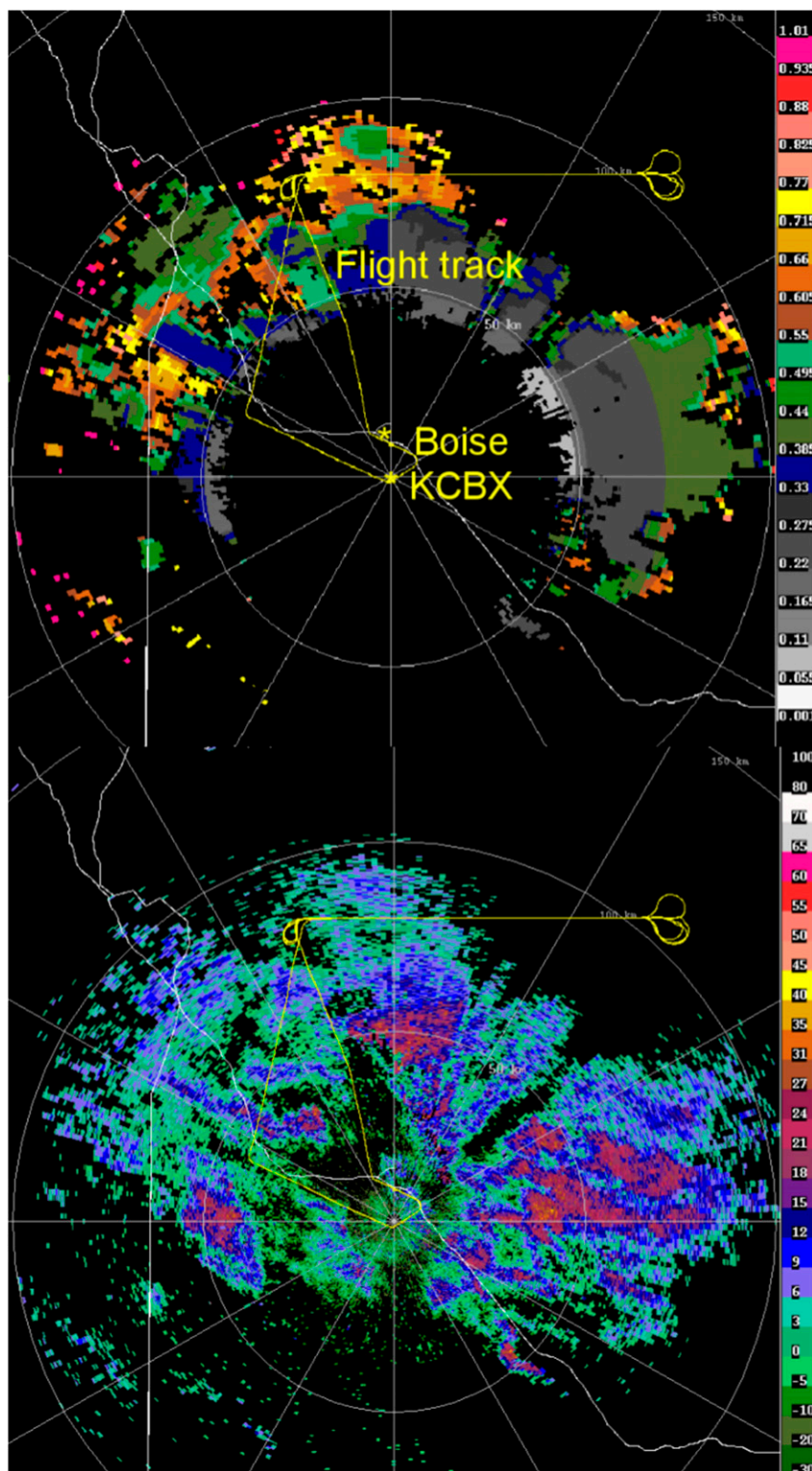


FIG. 10. (top) RadIA's interest in the presence of SLD (0–1 continuous, unitless) and (bottom) NEXRAD reflectivity (units: dBZ) on the 2.5° tilt at 2022 UTC 31 Jan 2017 from the KCBX NEXRAD (yellow) near Boise (yellow). The UWKA flight track is shown as a yellow line.

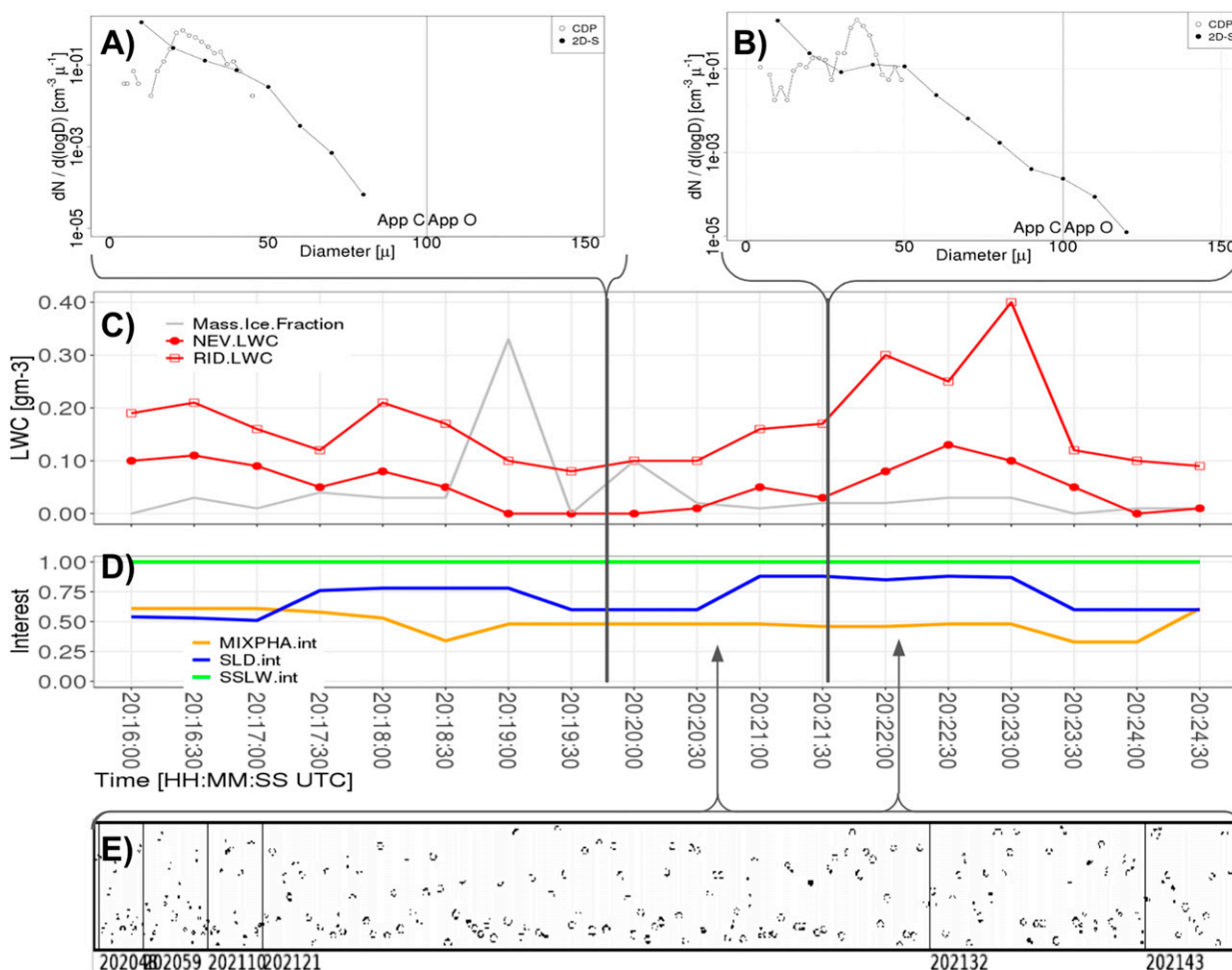


FIG. 11. CDP (open circles) and 2D-S (filled circles) particle size distributions at (a) 2019:50 and (b) 2021:30 UTC 31 Jan 2017, represented by the vertical black lines through the time series of (c) mass ice fraction (gray line), RID LWC (open red squares), and Nevzorov LWC (filled red circles), and (d) spatiotemporally matched RadIA interest values (green for small drop, blue for large drop, and orange for mixed phase). (e) A time series of 2D-S imagery of all particles with diameter greater than 100 μm during the whole period, all of which occurred between the two vertical black arrows.

efficient flight operations. Although RadIA is not an operational product, it has the capability to provide users with an accurate depiction of the presence of large and small drop SLW, as well as mixed-phase conditions at a very high spatial (NEXRAD has $\sim 250\text{-m}$ range gates, 0.5° azimuth beam separation) and temporal ($\sim 6\text{-min}$ repeated volume coverage) resolution.

Future work includes quantifying the degradation of SLD detection at higher radar tilt angles in stratiform conditions, as less range gates would intersect with precipitation sized particles. The RadIA codebase has been significantly streamlined over the past few years but still takes significant computing power to process data from individual radars in high-resolution polar coordinate data volumes. Another direction for future work is to explore the value of using ρ_{HV} as a feature field in the three RadIA algorithms. Though already utilized in FZLA, the field should provide value as a feature field in detecting homogeneous SSLW and SLD. Less clear is whether

ρ_{HV} would provide skill at detecting MIXPHA, as MIXPHA tends to be dominated by either solid or liquid particles.

Work needs to follow on whether RadIA can be computed using CONUS-wide Cartesian gridded mosaics of moments, which are computed by the National Severe Storms Laboratory as part of their Multi-Radar Multi-Sensor product suite. If a mosaic-based RadIA version could be shown to have sufficient skill, it would be possible to process CONUS-wide RadIA output with temporal resolution of 10 min or less. A freezing rain detection module could be added to RadIA following the work outlined in Van Den Broeke et al. (2016), which utilizes moment feature detection in quasi-vertical profiles of radar return. RadIA output was produced in real time in support of the 2019 In-Cloud Icing and Large-Drop Experiment, conducted in the Midwest of the United States, which included measurements from the National Research Council of Canada's Convair research aircraft and was sponsored by the FAA. This new dataset represents an opportunity to

verify and validate RadIA against an in situ dataset that represents more diverse IFI conditions that are not primarily orographic in origin. Also, RadIA output will be integrated into existing NCAR's Current Icing Potential (Bernstein et al. 2005) and testing needs to be conducted to quantify the improvements afforded. This merger could, for the first time, provide a three-dimensional volumetric measurement proxy of microphysics to CIP.

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APPENDIX

Abbreviations

a. Instruments, platforms, and algorithms

CDP	Cloud Droplet Probe
KA	King Air
OAP	Optical array probe (or 2DC, or 2D OAP)
ORPG	Open Radar Product Generator
RadIA	Radar Icing Algorithm

b. Organizations and campaigns

AWRP	Aviation Weather Research Program, part of the FAA
CSU	Colorado State University
FAA	Federal Aviation Administration
IPC	Idaho Power Company
NASA	National Aeronautics and Space Administration
NCAR	National Center for Atmospheric Research
NSF	National Science Foundation
SNOWIE	Seeded and Natural Orographic Wintertime Clouds: the Idaho Experiment
UW	University of Wyoming

c. Radar terminology

CHILL	Chicago Illinois radar
KCBX	Call sign for the Boise operational S-Band precipitation radar
K_{DP}	Specific differential phase; a comparison of the returned phase difference between the horizontal and vertical pulses; typically the range integration of ϕ_{DP} .
NEXRAD	Nickname for WSR-88D, "Next Generation Weather Radar"
ϕ_{DP}	Measured shift in phase of the polarized beams when it passes through liquid water

PPI	Plan position indicator
REFL	Reflectivity, the first radar moment
ρ_{HV}	Correlation coefficient (values: 0 to 1); a statistical correlation between the reflected horizontal and vertical power returns; a good indicator of regions where there is a mixture of precipitation types, such as rain and snow
WCR-3	Wyoming Cloud Radar, version 3, built by ProSensing, W band
WSR-88D	Weather Surveillance Radar-1988 Doppler
ZDR	Differential reflectivity moment

d. General terminology

AC	Aircraft
AGL	Above ground level
AZ	Azimuth
EL	Elevation
IFI	In-flight icing
ILW	Integrated liquid water
IOP	Intense observation period
LWC	Liquid water content
MSL	Mean sea level
SLD	Supercooled large drops (of maximum mean diameter equal to or larger than 100 μm)
SLW	Supercooled liquid water (of any mean diameter)
SSLW	Supercooled small-drop liquid water (of maximum mean diameter smaller than 100 μm)
V&V	Verification and validation

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