An Integrated Approach to Weather Radar Calibration and Monitoring Using Ground Clutter and Satellite Comparisons

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Abstract

The stability and accuracy of weather radar reflectivity calibration are imperative for quantitative applications, such as rainfall estimation, severe weather monitoring and nowcasting, and assimilation in numerical weather prediction models. Various radar calibration and monitoring techniques have been developed, but only recently have integrated approaches been proposed, that is, using different calibration techniques in combination. In this paper the following three techniques are used: 1) ground clutter monitoring, 2) comparisons with spaceborne radars, and 3) the self-consistency of polarimetric variables. These techniques are applied to a C-band polarimetric radar (CPOL) located in the Australian tropics since 1998. The ground clutter monitoring technique is applied to each radar volumetric scan and provides a means to reliably detect changes in calibration, relative to a baseline. It is remarkably stable to within a standard deviation of 0.1 dB.

1. Introduction

Radars are one of the most common and important instruments used in the atmospheric sciences. They work at high spatial (∼1 km) and high temporal resolution (10 min), providing four-dimensional information on the distribution of hydrometeors, precipitation intensity, and convective cloud dynamics. They are thus ideal tools for studying weather and climate processes, evaluating numerical simulations of precipitating cloud systems, and monitoring and nowcasting hazardous precipitation events. The C-band polarimetric radar (CPOL), stationed near Darwin (11°S, 131°E), northern Australia, since 1998, is an ideal tool for studying tropical convection (Keenan et al. 1998).

Yet, to be useful for these applications, it must be well calibrated.

The main quantity measured by radars is the radar reflectivity factor \( Z_m \) (dBZ):

\[
Z_m(r) = Z(r) + 2 \int_0^r a(r) \, dr,
\]

where \( r \) (km) is the radial distance, \( Z \) (dBZ) is the nonattenuated reflectivity factor, and \( a \) (dB km\(^{-1}\)) is the specific attenuation. The radar equation can be written in a simple form as (e.g., Probert-Jones 1962)

\[
Z_m = 10 \log C + 20 \log r + 10 \log P_r,
\]

where \( P_r \) is the returned power by the target and \( C \) is the so-called radar constant. The challenge of radar calibration is to estimate this constant \( C \) for given radar settings and its variations in real time. It depends on a
wide range of parameters, including wavelength, beamwidth, pulse length, transmitted power, and receiver gain. These quantities can vary over time as a result of degradation or maintenance of radar hardware. It is thus nearly impossible to estimate $C$ without using an external source of information.

CPOL, and all the radars of the Australian Bureau of Meteorology network, use a standard internal calibration procedure. However, these tests are performed at most a few times per year, with no rigorous calibration monitoring the rest of the time. As a result, while exploring the dataset we found 1) an abrupt change in radar calibration, 2) a long period of time where the radar is miscalibrated, and 3) large differences between radars with overlapping areas. It is for these reasons that we decided to find external ways to monitor the radar calibration, to be able to adjust the calibration quickly and accurately, and to have a common procedure for the entire operational network.

Over the years, many radar calibration techniques have been developed, using a fixed target (Atlas and Mossop 1960); collocated disdrometer data (Stout and Mueller 1968); solar interference (Whiton et al. 1976); high reflectivity gradients (Mueller 1977); ground clutter echoes (Rinehart 1978); or, for dual-polarization radar only, the self-consistency of polarimetric variables (Gorgucci et al. 1992). Joint observations of precipitating systems can also be used, by comparing with spaceborne radars (e.g., Anagnostou et al. 2001) or other surrounding systems that can also be used, by comparing with spaceborne radars (e.g., Anagnostou et al. 2001) or other surrounding radars (e.g., Vukovic et al. 2014). Radar calibration techniques are often evaluated separately. Yet, as proposed by Vivekanandan et al. (2003; Gourley et al. 2009). It uses elevation (or the temperature) or physical assumptions to be made regarding rain microphysics (e.g., the drop-shape model, the standard deviation of the canting angle). As will be shown later, assumptions in the drop-shape model and the canting angle are responsible for most of the variability of the self-consistency curves, and these variations can have an impact greater than 5 dB on the calibration of $Z_h$. We use our calibrated CPOL dataset as a reference to constrain these rain microphysics parameters.

In the present study we introduce an integrated approach called satellite and clutter absolute radar (SCAR) calibration to adjust the calibration of the reflectivity $Z_h$. We also introduce a broader framework for adjusting the calibration of the differential reflectivity $Z_{dr}$. For $Z_{dr}$, we use 1) ground clutter monitoring and 2) spaceborne radar echoes. Ground clutter monitoring is first used to adjust for calibration changes during periods of continuous operation. Comparisons with spaceborne radars are then used to determine the absolute calibration offset for each period. If satellite data are not available for a given place, or for a given season, then the self-consistency technique is used to provide an absolute value of calibration. For $Z_{dr}$, we use the birdbath technique, that is, vertically pointing scans in light rain (Gorgucci et al. 1999).

Radar calibration monitoring using ground echoes was first introduced by Rinehart (1978), but it has been experiencing a renewed interest since the studies of Silberstein et al. (2008), Marks et al. (2009), Melnikov and Zrnić (2015), and Wolff et al. (2015). It uses echoes from a multiplicity of ground targets close to the radar (generally within a 10-km range) to determine a baseline value of clutter reflectivity that is used to monitor changes in calibration. This is called the relative calibration adjustment (RCA) technique. The RCA technique provides a value for each radar scan but monitors changes in calibration relative only to a baseline.

To get the reference value of that baseline, we compare the ground radar observations of precipitating systems against spaceborne radars, and the Tropical Rainfall Measuring Mission (TRMM) (Kummerow et al. 1998) and Global Precipitation Measurement (GPM) mission satellites (Hou et al. 2014). The cross validation of reflectivity from TRMM or GPM with ground radar reflectivity measurements has been the subject of numerous studies. It has been used to assess the quality of precipitation radar (PR) estimations (e.g., Schumacher and Houze 2000; Liao et al. 2001; Park et al. 2015), to study PR sensitivity (Heymsfield et al. 2000), to develop attenuation algorithms (Liao and Meneghini 2009), and to calibrate ground radars (Anagnostou et al. 2001; Wang and Wolff 2009). The approach followed here is the volume-matching method of Schwaller and Morris (2011) as modified by Warren et al. (2018).

We then take advantage of our long-term calibrated radar dataset to assess the performance of the self-consistency technique (Gorgucci et al. 1992) and robustness to variations in the drop size distribution (DSD). A number of studies have used this method for radar calibration (e.g., Goddard et al. 1994; Scarchilli et al. 1996; Vivekanandan et al. 2003; Gourley et al. 2009). It uses the self-consistency, in light rain, of $Z_h$, $Z_{dr}$, and specific differential phase $K_{dp}$. The self-consistency technique allows for the estimation of one of these parameters given the other two. The principle of the technique is to estimate $Z_h$, $Z_{dr}$, and $K_{dp}$ from measurements of DSDs using disdrometer measurements, collected within the radar domain, and to perform scattering calculations using the transition (T)-matrix formulation of Mishchenko et al. (1996). Importantly, T-matrix calculations require knowledge of some parameters that can vary over time (e.g., the temperature) or physical assumptions to be made regarding rain microphysics (e.g., the drop-shape model, the standard deviation of the canting angle). As will be shown later, assumptions in the drop-shape model and the canting angle are responsible for most of the variability of the self-consistency curves, and these variations can have an impact greater than 5 dB on the calibration of $Z_h$. We use our calibrated CPOL dataset as a reference to constrain these rain microphysics parameters.
parameters and to assess the potential accuracy of the regionally tuned self-consistency technique.

This paper discusses development, adaptation, performance, and integration of these calibration techniques. Section 2 presents the instruments used in this study: CPOL, the nearby disdrometer, and the spaceborne radars on board TRMM and GPM. Section 3 describes the RCA technique, our new updates on the technique, and its results. Section 4 describes the TRMM and GPM comparison technique, and the iterative method we have developed to minimize the variations and improve its accuracy. In section 5 we review the self-consistency technique and its relevance for calibrating $Z_h$ and $Z_{dr}$. Conclusions are given in section 6.

2. Instrumentation and data

a. Darwin C-band weather radar

CPOL is a dual-polarization Doppler radar, working at a frequency of 5.6 GHz with a pulse repetition frequency of 1000 Hz and a beamwidth of 1°. CPOL is located at Gunn Point ($-12.245^\circ$N, $131.045^\circ$E), about 25 km northeast of Darwin International Airport. CPOL performs a set of scans with an update time of 10 min. This includes, nominally, a volume scan, a vertically pointing scan, and two RHIs. The scan comprises 15 elevations: 0.5°, 0.9°, 1.3°, 1.8°, 2.4°, 3.1°, 4.2°, 5.6°, 7.4°, 10.0°, 13.3°, 17.9°, 23.9°, 32.0°, and 43.1°. An additional series of scans at 90° is also performed regularly. The periodicity of the vertically pointing scan changes from season to season, and there are no such scans for seasons 2009/10 and 2010/11. The observed parameters are $Z_h$, $Z_{dr}$, Doppler velocity $v$, differential phase $\phi_{dp}$, spectrum width $\sigma_v$, and cross-correlation coefficient at zero lag $\rho_{v0}$. The maximum unambiguous range of the volume scan is 140 km with a range gate spacing of 250 m and an azimuthal beam spacing of 1°. Between 2001 and 2007, to reduce the data size and to allow real-time transmission to the regional forecasting office, the radar gate range was changed to 300 m, and data were sampled with an azimuthal resolution of 1.5°. Before 2007, the azimuthal indexing had to be corrected while, after 2007, the data are generated with the data synced to the azimuthal sampling. CPOL has produced more than 350 000 plan position indicator scans over 17 wet seasons (November–May). Because of its location in the tropics and long observational record, CPOL is a unique tool for research.

Internal calibration of CPOL is performed at the beginning of each wet season. Therefore, any change in radar calibration that could happen during a season cannot be tracked using internal calibration. It was a major motivation of this present work to monitor the CPOL calibration using external sources. The first step is to calibrate the receiver gain by injecting a known noise source and to adjust the noise level of CPOL. A single-point calibration procedure (injecting a known signal at a known injection point) is used to calibrate the receiver chain. In short, a known signal power is injected into the receiver via the forward port of the system’s bidirectional waveguide coupler. The system is made to record the response of the analog-to-digital converter, the receiver being linear means only a pair of points is needed to establish the transfer curve. Likewise, the transmitted power is checked from the same forward port of the bidirectional coupler. The unknowns between the transmitter and the receiver then reduce to the waveguide loss, antenna gain, and radome loss. A solar calibration procedure using the sun as a known backscattered-power target is then used to calculate the antenna gain and the waveguide losses. More details about these internal calibration procedures are available in Chandrasekar et al. (2015).

The calibration of CPOL, using our integrated approach, is evaluated for all available wet seasons between 1998 and 2017. During that period three seasons are missing: 2000/01, 2007/08, and 2008/09. The first season is missing because the radar was moved to Sydney, Australia, to support the 2000 Sydney Olympic Games (Keenan et al. 2003). The two latter seasons are missing because the radar antenna and receiver needed replacement. There are thus 17 wet seasons available out of this 20-yr period. Outside of the wet season, CPOL is shut down for maintenance because there is very limited precipitation.

The cross-correlation coefficient is corrected for low signal-to-noise ratio using an algorithm adapted from Bringi et al. (1983). The differential phase $\phi_{dp}$ is evaluated using the linear programming algorithm described in Giangrande et al. (2013). The attenuation on the horizontal reflectivity is corrected using the algorithm by Gu et al. (2011). The two latter techniques and algorithms are part of the Python ARM Radar Toolkit (Py-ART) (Helmus and Collis 2016). The specific differential attenuation $A_{dp}$ on $Z_{dr}$ is estimated using a linear $A_{dp} = K_{dp}$ relationship (Bringi et al. 1990).

b. Spaceborne precipitation radars

The Precipitation Radar (PR) on board TRMM operated almost continuously from December 1997 to April 2015, with reliable measurements up to September 2014 (Kummerow et al. 1998). Its minimal detectable reflectivity is around 18 dBZ. A scan is composed of 49 sample beams within the cross-track swath of 215 km prior to an orbit boost in August 2001 and 247 km
afterward. The horizontal resolution was 4.3 km before the boost and 5 km after (±17° from the path center), and the vertical resolution is 250 m. Version 7 of the 2A23 (precipitation type and brightband characteristics) and the 2A25 (corrected reflectivity) products are used for our comparisons. Precipitation type is determined using the horizontal and vertical echo structures (Awaka et al. 2009). To correct for attenuation, which is substantial in convective cores at Ku band, a hybrid method (Meneghini et al. 2004) combining the approach of Hitschfeld and Bordan (1954) and Meneghini et al. (2000) is used.

The GPM satellite carries the Dual-Frequency Precipitation Radar (DPR) working at Ka and Ku bands. The Ku-band radar is similar to the PR on TRMM, with a cross-track swath of 245 km. The nominal sensitivity of the KuPR is 18 dBZ, the same as TRMM (Hou et al. 2014); however, prelaunch tests showed that it could detect as low as 14.5 dBZ (Toyoshima et al. 2015). Version 5 of the 2AKu product has been used for this study. It is available from March 2014 onward, and it contains the same information as the 2A23 and 2A25 TRMM products.

c. Disdrometer

Observations of the drop size distribution from an impact disdrometer are used for the self-consistency technique. The disdrometer is located at the U.S. Department of Energy Atmospheric Radiation Measurement (ARM) central facility, near Darwin airport (−12.425°N, 130.892°E), about 25 km southwest of CPOL. A Python implementation of the T-matrix algorithm has been used to compute $Z_b$, $Z_d$, and $K_d$ from disdrometer measurements (Leinonen 2014). These results are then used to derive a self-consistent relationship for this tropical area.

3. The RCA technique: Using ground clutter to monitor reflectivity calibration

a. Introduction

Persistent echoes close to the radar are generally caused by buildings, roads, topographic structures, or biological markers like trees. For stationary clutter echoes ($r = \text{constant}$) with constant scattering properties ($P_r = \text{constant}$), it can be seen from Eq. (2) that any change in reflectivity over time must be due to a change in the radar constant:

$$\Delta Z_c = \Delta(10 \log C),$$  \hspace{1cm} (3)

where $Z_c$ is the ground clutter reflectivity. The main assumption of the RCA technique is that any variation in ground clutter reflectivity is caused by a change in radar calibration. A statistical analysis of the reflectivity of these fixed echoes can be used to monitor the radar calibration.

To use the RCA technique, a map of close-range clutter is first generated by looking at the position of high-reflectivity nonmeteorological echoes. We look only at the nonmeteorological echoes from the first elevation. Nonmeteorological echoes are defined by $\rho_{hv} < 0.5$ and $v = 0 \text{ m s}^{-1}$. The frequency of occurrence of ground clutter is then computed for the closest 10-km range around the radar for a set of clear-sky data to derive a “clutter map.” Wolff et al. (2015) proposed retaining only those pixels with a frequency of occurrence above 50%. Because there are numerous clutter points around CPOL, we applied a higher threshold of 95% so that only the most robust echoes are retained.

Once we have the position of permanent clutter echoes, we then parse the entire dataset and extract the reflectivity of the clutter echoes. Silberstein et al. (2008) proposed using the 95th percentile of the ground clutter reflectivity distribution to monitor the radar calibration. By determining a baseline for the clutter reflectivity distribution $Z_{c,\text{ref}}$, we can determine the relative calibration offset (Silberstein et al. 2008; Wolff et al. 2015):

$$\text{RCA}_{\text{offset}} (\text{dB}) = Z_{c,\text{ref}} - \text{CDF}[Z_c, 95\%],$$  \hspace{1cm} (4)

where CDF[$Z_c$, 95%] is the 95th percentile of the ground clutter reflectivity, called the RCA value. The RCA value is the offset that has to be applied to the reflectivity in order to obtain agreement with the established baseline.

Figure 1 shows the clutter selection procedure for three different seasons: 1998 (Figs. 1a–c), 2006 (Figs. 1d–f), and 2013 (Figs. 1g–i). The left column is the mean reflectivity of all nonmeteorological echoes for 1 week of data, the center column is the frequency of occurrence (%) of each echo, and the right column is the derived clutter map (i.e., $Z_b > 40 \text{ dBZ}$ and $f > 95\%$). The clutter mask of 2006 retains 3034 points (Fig. 1f), while the clutter masks of 1998 and 2013 retain around 1000 points (Figs. 1c, i). This is caused by a problem with the CPOL elevation angle drive. Both Silberstein et al. (2008) and Wolff et al. (2015) denoted that the RCA could also be used to monitor change in the elevation angle, as the RCA is very sensitive to it. By varying the elevation angle from 0.9° to 0.8°, they found a 1-dB increase in the RCA value. The RCA value for CPOL increases more during that period, by almost 5 dB, but we are looking at clutter with a much lower elevation angle; therefore, we probably have a more direct, and thus higher, clutter reflectivity.
These different masks, shown in Figs. 1c, 1f, and 1i, impact the RCA value, because the clutter reflectivity distributions are different. In fact, if the mask of 1998 is used on data from 2013 while being similar at face value, it causes the RCA values to change by 4 dB. The RCA baseline of one season should not be compared to another if the clutter maps are different. In the following work, we always treated each season independent of one another and made a new clutter mask at the beginning of each season.

b. Impact of rain on ground clutter reflectivity

1) DAILY VARIATIONS

Wolff et al. (2015) suggested that precipitation had little to no effect on the RCA technique, as the associated reflectivities are usually considerably lower than the 95th percentile of the ground echo reflectivity. However, no quantitative study was conducted to quantify this effect. So, to study the impact of precipitation on our RCA value, we have estimated the average rainfall rate within a 5-km range from the radar. Because we are working with the raw, uncorrected, and uncalibrated data (i.e., the calibration has not been adjusted with an external source, and noise and anomalous propagation have not been removed), only a rough estimation of rainfall rate is achievable, sufficient for the purpose of this sensitivity analysis. A general $Z$–$R$ relationship, $Z = 300R^{1.35}$ (Jorgensen and Willis 1982) is used to estimate the rainfall rate.

Figure 2a shows the maximum, mean, median, and 95th and 99th percentiles of the ground clutter reflectivity distribution. Figure 2b shows the average rainfall rate for the first 5-km range around the radar, for CPOL, for all scans from 1 January 2017. Figure 2b indicates that there is no precipitation above the radar site before noon. Of all the different statistics for the ground clutter reflectivity distribution (Fig. 2a), the 95th percentile and the 99th percentile, as well as the maximum, stay stable when there is precipitation. In Fig. 2a, during the dry period, the 95th and 99th percentiles, and the maximum have values of $44.0 \pm 0.1$, $47.1 \pm 0.4$, and...
50.8 ± 0.6 dBZ, respectively. During the wet period, the 95th and 99th percentiles, and the maximum have values of 43.7 ± 0.4, 46.3 ± 0.9, and 50.4 ± 1.2 dBZ, respectively. Clearly, the 99th and 95th percentiles are the least impacted by precipitation. During the dry period, the rate of precipitation shows almost no variability. The variability during rain period is more important; we can see a drop at the 95th percentile of about 2.5 dB at 1200 UTC (the beginning of rain) and drops of 3–4 dB at about 1300–1400 UTC. It returns to its baseline value afterward. Even if these drops in 95th percentiles are relatively important, because they are localized, the daily statistics are only slightly affected. The variations caused by rain on the whole day are of about 0.4 dB. Yet, it is easy to remove scans contaminated with rain close to the radar and the user of the RCA technique should do so. Moreover, it validates the idea, proposed by Silberstein et al. (2008), to use the 95th percentile of ground clutter reflectivity for monitoring the radar calibration.

c. Seasonal monitoring of the radar calibration

The RCA technique can be used to monitor radar calibration and pinpoint times when it changes. Because of the sheer number of scans performed every day, estimating the daily mean of the RCA value is a more sensible approach to reduce radar noise and fluctuations in the nature of clutter (moving trees for instance). This daily averaging acts to smooth RCA values and makes the impact of rain even more negligible (not shown). Thus, discrimination between wet and dry scans is not shown anymore, and the RCA is computed for all scans.

The 17 seasons of CPOL data are processed using the RCA technique. Most seasons show a similar pattern: long periods of time when the RCA is stable around a value, which becomes the de facto seasonal baseline, with interleaving shorter-duration periods when the RCA value is higher or lower (e.g., Fig. 4 for season 2013/14). Figures 4 and 5 show the RCA value for all radar scans, the daily average, and the daily variations of the RCA value relative to a baseline, for seasons 2013/14 (Fig. 4), and 2015/16 (Fig. 5). These figures show how stable the RCA value is, even if episodes of rain are not excluded. The standard deviation of the daily RCA values, for the baseline period, in 2013/14 is 0.03 dB
(Fig. 4b) and 0.04 dB for 2015/16 (Fig. 5b). The date and the value of changes in calibration, compared to the RCA baseline value, are represented by red dots in Figs. 4c and 5c.

For season 2013/14, the first day of measurement is 16 October 2013, and for the first 2 days, CPOL’s RCA value is around 47.8 dB. Then, from 18 October to 5 November 2013, the RCA value increases to 49.2 dB. After 5 November, the RCA shows an unique stable value of 47.7 dB. This last value is the baseline for season 2013/14. The data are corrected for seasonal variations of the calibration by offsetting the reflectivity toward the
baseline every time the reflectivity distribution differs from the baseline. For Fig. 4, it concerns the period from 18 October to 5 November 2013. These two days correspond to modifications to the CPOL calibration by the radar engineer on site.

In 2015/16, after the first day of data, the RCA value remains stable for the rest of the season (Fig. 5). Between 12 November and 15 December 2015, one can notice a drop in the RCA value, and this is particularly visible in Fig. 5b. This change has not been corrected, as it is below our somewhat conservative threshold value of 0.5 dB. Yet, it clearly demonstrates the sort of accuracy that can be achieved with the RCA technique. We should note that even though the statistics behind the RCA give results with low variability, the radar quantization of the reflectivity is 0.5 dB. Even though the RCA can monitor change below 0.5 dB, it still means that the accuracy of the RCA technique is bound by the quantization of radar data, thus 0.5 dB.

Although the RCA technique allows for accurate monitoring and adjustment of reflectivity offset changes, it provides only a relative calibration, as the baseline is not compared to an external reference of reflectivity. To estimate a reference value of calibration offset for that baseline, we use comparisons with spaceborne radars.

4. Calibrating CPOL reflectivities with spaceborne radars

The ground radar (GR) calibration technique using TRMM and GPM PR reflectivity measurements as the external reference is described in detail in Warren et al. (2018). TRMM and GPM reflectivity is corrected from the attenuation. In short, it is a volume-matching method that allows quantitative comparison of the reflectivity of spaceborne radars (SR) and ground radars, with minimal spatial processing of the two datasets. Intersections between the radar beams are identified and the reflectivities from both instruments are spatially averaged to an approximately common sample volume.

We use the same set of requirements as in Warren et al. (2018). The maximum delay between spaceborne and ground radar measurements is 300 s. A minimum of 10 satellite profiles inside the ground radar area is required for comparison. This corresponds to a surface area of about $250\,\text{km}^2$. The only notable differences with Warren et al. (2018) are that we compare only the liquid phase. Warren et al. (2018) suggested that there may be overcorrection of attenuation in heavy stratiform rain (reflectivities above $36\,\text{dBZ}$); however, for most stratiform samples (which have lower reflectivities), the agreement was good and attenuation (and thus the correction) is minimal. We found good agreement between GR and SR reflectivity above and below the bright band in stratiform precipitation and so used both in our previous study. However, because these frequency conversions of the reflectivity tend to be less accurate for the ice phase than for the liquid phase, we decided in the present paper to exclude the ice phase as well (CPOL being located in the tropics, we have enough values in the liquid phase). In convective precipitation, Warren et al. (2018) found a systematic decrease in GR–SR reflectivity with height, suggesting a systematic undercorrection of
attenuation at low levels. Therefore, convective samples were excluded from the analysis.

The reflectivity of spaceborne radars is converted to C band by using results from the T-matrix calculation (more details on the T-matrix parameterization in section 5). The T matrix allows us to compute the reflectivity from the disdrometer measurements at C and Ku bands. As shown in Fig. 6, using a similar method as Cao et al. (2013) for converting reflectivity from Ku to S band, we found that the dual-frequency ratio (DFR) between the C and Ku bands can be approximated by a fourth-order polynomial:

$$\text{DFR}(x) = 1.21 \times 10^{-6} x^4 - 1.23 \times 10^{-3} x^3 + 6.38 \times 10^{-3} x^2 - 0.15 x + 0.53$$

where $x$ is the Ku-band reflectivity. Therefore, the C-band reflectivity is $Z_C = Z_{Ku} + \text{DFR}(Z_{Ku})$. The accuracy of this conversion is about \pm 0.5 dB for $10 \leq Z < 30$ dBZ and about \pm 1 dB for $Z > 30$ dBZ (Fig. 6). Note that this relation is valid for $Z \in [10; 60]$ dBZ, for the liquid phase only, and in the tropics.

TRMM PR data have been used for seasons between 1998 and 2014, while GPM PR data have been used for seasons after 2014. Because of our stringent requirements, between 15 and 30 cases match for comparison each season.

a. GR–PR comparison for one match

Figures 7a and 7b show the probability density functions (PDFs) of CPOL and TRMM reflectivities for 19 January 2014 before (Fig. 7a) and after (Fig. 7b) calibrating CPOL. Figures 7c and 7d show the PDF of reflectivity difference between CPOL and TRMM ($\Delta Z_h = Z_h^{[\text{GPM}]} - Z_h^{[\text{CPOL}]}$), before (Fig. 7c) and after (Fig. 7d) CPOL calibration. Before calibration, Figs. 7a and 7c clearly show that CPOL is running with TRMM or GPM. For the volume-matching technique, only space radar reflectivities above this level are included in the calculation. A threshold of 10 dBZ is taken for the GR reflectivity. Warren et al. (2018) showed that the reflectivity differences derived using the volume-matching method can vary substantially (by more than 1 dB) depending on the value of the GR reflectivity threshold. If $\Delta Z_h > 0$, then some points that were ignored because of the reflectivity threshold may now be part of the $Z_h$ distribution. Conversely, if $\Delta Z_h < 0$, then some points of the CPOL $Z_h$ distribution that were included may be now dismissed. To mitigate this effect, we use a similar iterative procedure as the one present in Warren et al. (2018), based on Protat et al. (2011), which largely reduced the variation between the GR and PR reflectivity distributions.

The correction procedure shown in Fig. 8 (the SCAR-integrated approach) works this way: 1) we use the RCA technique to correct toward one baseline all the variability in the radar calibration for one season (section 3). 2) We use the volume matching presented herein and determine the $\Delta Z_h$ offset needed to obtain agreement with TRMM or GPM. 3) If $|\Delta Z_h| \leq 0.5$ dB, then the procedure stops and CPOL is considered calibrated. If not, then an offset equal to $\Delta Z_h$ is applied on CPOL reflectivity and the whole comparison is started again until $|\Delta Z_h| \leq 0.5$ dB. A maximum of three iterations was required to achieve convergence for all seasons in the CPOL dataset. This iterative procedure was found to reduce the standard deviation of the $\Delta Z_h$ distribution and thus to achieve a better statistical agreement between CPOL and TRMM–GPM.

b. GR–PR comparison for one season

The SCAR-integrated method allows us to automatically adjust the calibration of ground radars. Here we detail how we use it on one season (2013/14) of data. PDFs of $Z_h$ and $\Delta Z_h$ are evaluated every time there is a match between CPOL and TRMM–GPM. Figure 9a
shows the time series of $D_{Zh}$ for the uncalibrated CPOL data over season 2013/14. The seasonal average is computed for the whole period. Because the sample size can be very different for each match, we also calculated the weighted average. The sample size on 20 and 23 November, 30 December, and 12 March is 3868, 728, 1234, and 2931 volumes, respectively, while it is below 150 for the other dates.

By weighting the seasonal $D_{Zh}$ average with the sample size, $D_{Zh} = 0.6 \text{ dB}$, while the nonweighted average is $D_{Zh} = 0.7 \text{ dB}$, with all matches included $D_{Zh} = 1.3 \text{ dB}$, with the first match (5 November 2013) excluded.

To obtain the results displayed in Fig. 9b, we correct $Z_h$ from the variations found by the RCA. Because the RCA technique shows a stable value of 47.5 dB after 7 November 2013 (cf. Fig. 4), this value is used as a baseline to correct CPOL reflectivity for season 2013/14. It means that CPOL reflectivity between 18 October and 6 November 2013 is adjusted by the value of the RCA offset [cf. Eq. (4)]. Figure 9b clearly shows that the first match (5 November 2013) has been shifted to similar values as those afterward. The other matches are not affected by the RCA correction, as their RCA value is already the RCA baseline.

We then use the value of 0.9 dB found for the weighted average in Fig. 9b as an offset to GR reflectivity. Finally, we run the volume-matching technique once again to get Fig. 9c. Because the new season average is below $|\Delta Z_h| = 0.5 \text{ dB}$, the procedure stops and the reflectivity is considered calibrated after the second iterative pass. The weighted seasonal $D_{Zh}$ average is actually the offset
that is needed to transform the RCA baseline into the reference value of calibration, for that season. Note that if we had used a baseline of about 46.5 dB for the RCA, then we would have immediately reached an agreement between GR and TRMM PR reflectivities. This is consistent all along the period between 2009 and 2014 (period for which TRMM is used for comparison). However, this is an a posteriori result and we would not have been able to find this baseline value with the RCA technique alone.

c. Comparison of TRMM–GPM and CPOL between 1998 and 2017

The SCAR-integrated method has been applied to the entire CPOL dataset, between 1998 and 2014. Figure 10 shows the comparison of the reflectivity distribution of CPOL against TRMM from 1998 to 2014 (Figs. 10a,c) and GPM from 2014 to 2017 (Figs. 10b,d) before (Figs. 10a,b) and after (Figs. 10c,d) CPOL calibration. The comparison with TRMM corresponds to 301 matches (34 for GPM) for a total of more than 255,000 individual volume-matched samples (20,000 for GPM). For TRMM, the Pearson correlation coefficient $r$ before calibration is 0.78 (0.89 for GPM); data are scattered and several peaks in the density distribution can be observed. After calibration, Fig. 10c shows that CPOL and TRMM are in much better agreement (Fig. 10d for GPM), with $r = 0.90$ (0.91 for GPM) and less scatter around the 1:1 line.

In conclusion, the use of the RCA technique, for correcting precisely all the daily variations to a unique baseline, coupled with the satellite volume-matching method, to find the reference calibration value of that baseline, has been shown to be a robust approach to calibrate ground radars.

5. Disdrometer-based approaches

Gorgucci et al. (1992) first noted a very robust relationship between $K_{dp}/Z_h$ and $Z_{dr}$ in rain, which was referred to as the “self-consistency” relationship, later generalized by Scarchilli et al. (1996) and Gorgucci et al. (2006). Various studies then used the self-consistency approach for calibrating radars (Goddard et al. 1994; Vivekanandan et al. 2003; Gourley et al. 2009; Marks et al. 2011, among others). To develop a relationship for our geographical location, we first compute a self-consistency relationship using our calibrated CPOL dataset, where $Z_h$ is calibrated using the method presented previously, and $Z_{dr}$ is calibrated using the birdbath technique. Next, we use data from an impact disdrometer present in 2006 at the Darwin ARM site (about 25 km southwest of CPOL) to derive a set of self-consistent relationships using T-matrix calculations and different values of the standard deviation of the canting angle and different drop-shape models available in the literature. We then assess which set of assumptions best approximates the reference CPOL self-consistent relationship. Third, we assess the suitability of the self-consistency technique for calibrating $Z_h$. Finally, we use the CPOL dataset and the self-consistency to assess the potential of this self-consistency technique for $Z_{dr}$ calibration.

a. The self-consistency technique

The polarimetric variable $\phi_{dp}$ is processed using the algorithm of Giangrande et al. (2013). This method applies a Sobel filter to compute $K_{dp}$, to smooth the data, and to mitigate the impact of the noise on the retrieval. The same smoothing filter has been applied
to $Z_h$ and $Z_{dr}$ for consistency. We use the same criteria from Table 1 in Gourley et al. (2009) to CPOL polarimetric variables prior to estimating the self-consistency relationship. In short, we rejected rays that have $Z_h > 50$ dBZ, $Z_{dr} > 3.5$ dB, and $\phi_{dp} > 12^\circ$. We also looked only at the first 70 km of range, for rain only. The maximum diameter considered for the calculation of $Z_h$ is the default 9 mm; however, we note that the maximum measured raindrop diameter is only 5.4 mm.

Figure 11 shows the normalized density histogram of $K_{dp}/Z_h$ versus $Z_{dr}$ for CPOL in 2006, that is, the same year as the disdrometer measurements used later for comparisons. The reflectivity in natural units (mm$^6$ m$^{-3}$) is used here. The sample size is greater than 180 million data points. The black curve is a third-order polynomial fit to CPOL data:

$$f(x) = 10^{-6} \times (-0.78x^3 + 6.74x^2 - 22.4x + 49.9),$$

where $x$ is $Z_{dr}$. Data for $Z_{dr} < 0.5$ dB or $Z_{dr} > 2.5$ dB are much sparser and this does not allow an accurate fit of the self-consistency curve for CPOL. This is due to the criteria used to select regions with sufficiently large differential phase but not too large to avoid any potential effect from attenuation and differential attenuation. This curve is our reference for deriving the optimal set of assumptions using the T-matrix disdrometer calculations. For the sake of comparison, the Gourley et al. (2009) midlatitude relationship is shown. Large differences are found. This important result highlights the need to derive local self-consistent relationships to use this approach. If the Gourley et al. (2009) relationship were used to calibrate CPOL, then a 2-dB underestimation would result.
b. Parameterization of the T-matrix formulation using disdrometer data

The raindrop-shape model, the temperature, and the standard deviation of the canting angle std(C) of raindrops need to be assumed to derive polarimetric radar variables using T-matrix simulations from disdrometer observations. Observed counts from the disdrometer are used as input to the T-matrix simulations in this study. Yet these parameters can be difficult to ascertain and all depend on the local microphysics of rain. In the following, we compare results using three different temperatures $T = 0\degree$, $10\degree$, and $20\degree$C. Bringi et al. (2008) showed, using 2D video disdrometer, that in moderate wind conditions, the peak of the std(C) distribution is between $7\degree$ and $12\degree$ but with values that range from $4\degree$ to $20\degree$. Generally a value of $10\degree$ is used in the literature for calibrating radars with the self-consistency (Bringi and Chandrasekar 2001). Because we want to study how std(C) impacts the self-consistency results, we consider all std(C) values ranging from $1\degree$ to $30\degree$ in $1\degree$ increments.

Figure 12 shows the variation (%) caused by temperature on the self-consistency curves. More precisely,

$$V(X) = 100 \times \frac{X(20\degree) - X(0\degree)}{X(0\degree)},$$

where $X$ is the self-consistency function for a given temperature. The temperature is responsible for the dispersion of self-consistency curves for high $Z_{dr}$ values, but it does not have a significant impact for $0.5 < Z_{dr} < 2$ dB, where the majority of the radar data lies. Thus, the temperature impact can be neglected, and $T = 20\degree$C is taken hereafter.

Figure 13 shows the T-matrix results for six different raindrop-shape models. The six representative raindrop-shape models shown in Fig. 13 are those often used in the literature (Beard and Chuang 1987; Brandes et al. 2002; Goddard et al. 1982; Pruppacher and Beard 1970; Thurai et al. 2007; Thurai and Bringi 2005). Note that the

\begin{figure}[h]
\centering
\includegraphics[width=\textwidth]{fig10}
\caption{Density plots of the comparison between CPOL reflectivity and (a),(c) TRMM, and (b),(d) GPM reflectivities for (a),(b) before and (c),(d) after calibration. The individual volume-matched samples are about 255,000 for TRMM and 20,000 for GPM. The dashed lines represent ±1 dB from perfect correlation.}
\end{figure}
Thurai et al. (2007) model is actually based on the Beard and Kubesh (1991) model. The scatterplots seen in Fig. 13 show the results given by the T-matrix for $T = 20^\circ C$ and std($C$) = 5. The different colored curves are third-order polynomial fits of the T-matrix results for the same temperature but for different std($C$). For the sake of clarity, only std($C$) = 5, 10, 15, and 20$^\circ C$ are shown. The plain black curve is the CPOL polynomial fit from Fig. 11. In Fig. 13, all raindrop-shape models show a high dispersion around their inflexion point, but the Pruppacher and Beard (1970) and Thurai and Bringi (2005) models seem to have an unrealistic behavior for $Z_{dr}$, 0 dB. The former model was already noted as a source of error in Gourley et al. (2009). Even though Thurai and Bringi (2005) claimed that their model was not very different from the Brandes et al. (2002) model, Fig. 13 shows that small differences in the model parameterization cause important variations in the T-matrix results. Based on these results, the Pruppacher and Beard (1970) and Thurai and Bringi (2005) raindrop-shape models are excluded from further analysis.

To find the best std($C$) value for the T-matrix retrievals, we compute the root-mean-square (RMS) error of these retrievals against the self-consistency of CPOL data. Figure 14 shows the RMS error as a function of std($C$) for the Beard and Chuang (1987), Brandes et al. (2002), Goddard et al. (1982), and Thurai et al. (2007) raindrop-shape models. The Brandes et al. (2002) raindrop-shape model shows the smallest RMS error of all distributions for std($C$) = 12$^\circ C$. The Thurai et al. (2007) and Beard and Chuang (1987) models also present small RMS errors, but for higher std($C$), 15$^\circ C$ and 18$^\circ C$, respectively. However, these two models have a higher bias than the Brandes et al. (2002) model. As for the Goddard et al. (1982) model, even though it has a higher RMS error than the other models, its minimal RMS error is around 10$^\circ C$ and it shows almost no variation for std($C$) $\leq$ 12$^\circ C$, while all the other models have a well-defined minimum and diverge quickly from it.

To assess how well the T-matrix simulations reproduce the CPOL polarimetric data, we compute the reflectivity that would be measured if the polarimetric variables $K_{dp}$ and $Z_{dr}$ follow the self-consistency curves shown in Fig. 13. This is shown in Fig. 15 for Brandes et al. (2002) (Fig. 15a), Thurai et al. (2007) (Fig. 15b), Goddard et al. (1982) (Fig. 15c), and Beard and Chuang (1987) (Fig. 15d) raindrop-shape models for std($C$) = 12$^\circ C$, 15$^\circ C$, 18$^\circ C$, and 10$^\circ C$, respectively. This self-consistent $Z_h$ (dBZ) is defined as

$$Z_h = 10 \log_{10} \left[ \frac{K_{dp}}{f(Z_{dr})} \right], \quad (8)$$

where $f$ is the fit of a given self-consistent curve. In Fig. 15 the self-consistent curve is as follows:

for Brandes et al. (2002) (Fig. 15a):

$$f(x) = 10^{-5} \times (-0.23x^3 + 1.577x^2 - 4.577x + 6.607), \quad (9)$$

for Thurai et al. (2007) (Fig. 15b):

$$f(x) = 10^{-5} \times (-0.21x^3 + 1.516x^2 - 4.527x + 6.051), \quad (10)$$
FIG. 13. Density plots of the T-matrix results at $T = 0^\circ$C and std($C$) = $5^\circ$ for six different raindrop-shape models. The colored curves are the polynomial fits of the T-matrix results for $T = 20^\circ$C, and std($C$) = $5^\circ$, $10^\circ$, $20^\circ$, and $30^\circ$. The solid black curve is the fit of CPOL data from Fig. 11. The raindrop-shape models are (a) Beard and Chuang (1987), (b) Brandes et al. (2002), (c) Goddard et al. (1982), (d) Pruppacher and Beard (1970), (e) Thurai et al. (2007), and (f) Thurai and Bringi (2005).
for GODDARD ET AL. (1982) (Fig. 15c):

\[ f(x) = 10^{-5} \times (-0.23x^3 + 1.260x^2 - 0.985x + 2.942), \]  \hspace{1cm} (11)

and for BEARD AND CHUANG (1987) (Fig. 15d) raindrop-shape models:

\[ f(x) = 10^{-5} \times (-0.57x^3 + 3.369x^2 - 7.327x + 7.139), \]  \hspace{1cm} (12)

where \( x = Z_{dr} \), and \( f \) is valid for \( 0.5 < Z_{dr} < 3.5 \) dB.

Figure 15 clearly shows that the reflectivity retrieved by means of the self-consistent curves and the reflectivity measured by CPOL are in very good agreement for \( 10 < Z_h < 30 \) dBZ. Within this reflectivity range, the BRANDES ET AL. (2002) (Fig. 15a) and the GODDARD ET AL. (1982) (Fig. 15c) raindrop-shape models show correlation coefficients of 0.95 and 0.94, respectively. We suspect that for \( Z_h > 30 \) dBZ, departure from the 1:1 line is caused by C-band attenuation, while for \( Z_h < 10 \) dBZ, the differences probably come from the raindrop-shape model, where there is an important uncertainty for low \( Z_{dr} \) values (and thus lower \( Z_h \) values). As for the THURAI ET AL. (2007) and BEARD AND CHUANG (1987) raindrop-shape models, their lower correlation coefficients could be explained by Figs. 13a and 13e, respectively, as these figures imply that \( \text{std}(C) = Z_{dr} \) dependent for the CPOL data curve. More precisely, for the CPOL curve on these models, \( \text{std}(C) \sim 20^\circ \) for \( Z_{dr} < 1 \) dB, while \( \text{std}(C) < 10^\circ \) for \( Z_{dr} > 2 \) dB. Because the maximum of the CPOL data distribution is found for \( 1 < Z_{dr} < 2 \) dB, the THURAI ET AL. (2007) and BEARD AND CHUANG (1987) models fit very well here but strongly diverge elsewhere.

In view of the results, we use in what follows the BRANDES ET AL. (2002) raindrop-shape model for \( T = 20^\circ \)C and \( \text{std}(C) = 12^\circ \) as our best estimate for the T-matrix calculations. We have computed monthly values of the self-consistency of CPOL and found no remarkable differences within or between seasons. Even the period between 2002 and 2007, when the data resolution was changed, is similar to the other periods.

c. Using the self-consistency curves to monitor \( Z_h \)

Now that the T-matrix simulations have been tuned to match the reference CPOL self-consistent relationship, we assess in what follows the usability of this technique to monitor the reflectivity calibration. To do so, we artificially add an offset, ranging from –3 to 3 dB, to the reflectivity computed by the T-matrix algorithm, represented by the dashed curves in Fig. 16, still for year 2006. We also added an offset to the reflectivity measured by CPOL, as shown in Fig. 16 for an offset of 3 (Fig. 16a), 0 (Fig. 16b), and –3 dB (Fig. 16c). Figure 16 clearly shows that any change from the reference value of calibration is not only detected but also properly estimated by the self-consistent curves from the T-matrix computations. The curves in Fig. 16 can thus be used to estimate the offset needed to calibrate \( Z_h \) with an accuracy better than 1 dB.

d. Using the self-consistency curves to monitor \( Z_{dr} \)

As discussed previously, the principle of the self-consistency is that when two parameters out of \( K_{dp}, Z_h \), and \( Z_{dr} \) are known, the third one can be estimated. In the previous sections, we have used the self-consistency technique to calibrate \( Z_h \) if \( K_{dp} \) and \( Z_{dr} \) are known and calibrated, respectively. When \( Z_h \) and \( K_{dp} \) are known, then in principle the self-consistency approach can be used to calibrate \( Z_{dr} \). To illustrate the potential of monitoring the calibration of \( Z_h \) using self-consistency principles, we use calibrated CPOL data from the season 2016/17. It must be noted that selecting other seasons led to the same results. We also used the birdbath technique for the same period to estimate a reference \( Z_{dr} \) calibration to compare with the self-consistency. The birdbath technique finds that the \( Z_{dr} \) bias is \( 1.2 \pm 0.2 \) dB for the entire 2016/17 season.

Figure 17a shows the self-consistency of the radar data for November 2016. The dotted lines represent the self-consistency curves, computed from disdrometer
data, with an offset ranging from −0.5 to 1.5 dB, in increments of 0.5 dB, added to \( Z_{dr} \). The −1.2-dB offset on \( Z_{dr} \) detected by the birdbath calibration technique is clearly identifiable in Fig. 17a. As in Fig. 16 for the reflectivity, a set of various offset curves can be computed for \( Z_{dr} \) (Fig. 17a).

To quantitatively assess the potential of the self-consistency technique to estimate the calibration offset of \( Z_{dr} \) to within the required accuracy of 0.1–0.2 dB, we compute \( \Delta Z_{dr} = K_{dp}/Z_{hi} - f(Z_{dr}) \), where \( f(Z_{dr}) \) is Eq. (9), that is, the distribution of differences between the self-consistency relationship of CPOL data compared to the T-matrix disdrometer retrievals for November 2016 (Fig. 17b). The red line in Fig. 17b represents the \( Z_{dr} \) calibration value found using the birdbath technique. The \( Z_{dr} \) calibration offset found by the self-consistency technique is 1.2 ± 0.2 dB, that is, the exact same offset found by the birdbath technique. Thus, both techniques can be used successfully to monitor \( Z_{dr} \) calibration, provided that \( Z_{hi} \) is carefully calibrated before using the self-consistency technique. However, the amount of data required to calibrate \( Z_{dr} \) using the self-consistency technique is much larger than for the birdbath technique. In both cases we used 1 month of data (January 2017), but for the birdbath technique this amounts to only 15 000 points compared to around 100 million for the self-consistency. To assess how many data points are required to reach a calibration accuracy better than 0.2 dB with the self-consistency approach, we have applied the self-consistency \( Z_{dr} \) calibration technique daily, then in groups of increasingly more days within the test month of January 2017, up to 1 week. Our results indicate that when using 1 day, the self-consistency technique cannot calibrate \( Z_{dr} \) to better than about 0.5 dB, while in contrast the right offset of −1.2 could be retrieved when using 5 days or more of rainy data. Repeating the same procedure to other months of data yielded the same conclusions. Therefore, in conclusion, although when possible the birdbath technique should obviously be the preferred technique for \( Z_{dr} \) calibration, the self-consistency approach can be applied to chunks of 5 days or more of rainy periods to calibrate \( Z_{dr} \) to an accuracy better than 0.2 dB.
e. Calibration using scattering simulations of $Z_h$ with permanent disdrometer observations

With the self-consistency technique, we use measurements from a disdrometer to find the parameterization that best fits our calibrated radar. Once the self-consistency is correctly parameterized, the disdrometer is not needed anymore, as the radar reflectivity is then compared to the self-consistent curve.

The more conservative way to calibrate radar with the disdrometer is to compare radar reflectivity with scattering simulations of the reflectivity from the disdrometer (e.g., Stout and Mueller 1968). The fundamental problems with comparing reflectivities from the surface disdrometer and the scanning radar are as follows: 1) the radar senses well above the surface and the drop size distribution (i.e., reflectivity) can evolve as precipitation falls to the surface, and 2) these instruments have different spatial...
(the disdrometer is just one point) and temporal resolutions (about 1 min for the disdrometer). This would not be a problem if the precipitation was not varying in time and space. But since precipitation is variable at different temporal and spatial resolutions, the uncertainties from each instrument will be a combination of the instrument measurement error and the spatio-temporal variability of the precipitation (Williams et al. 2005).

Figure 18a shows the time series of the comparison between CPOL reflectivity and the disdrometer reflectivity, and Fig. 18b shows a histogram comparing the reflectivity between the two instruments. The disdrometer data have been resampled to the same frequency as the radar data (10 min). In total, there are 299 matches between the disdrometer and the radar. We removed disdrometer samples with a standard deviation above 10 dB, leaving 284 matches for comparison. The reflectivity of the pixel directly above the disdrometer site and its direct adjacent neighbors (eight of them) are averaged for comparison. The reflectivity calibrated by the RCA and the comparison with TRMM as input. Figure 18 shows that the mean difference between CPOL and the disdrometer is around 0.2 dB, but the standard deviation is around 3.7 dB. Figure 18b also shows a good correlation between the two instruments \((r = 0.86)\) but with large variability. This implies a similar conclusion as in Williams et al. (2005) and Frech et al. (2017), that although there is large variability between matched observations, the comparisons with the disdrometer are still meaningful. However, it appears clearly that uncertainties associated with this simple disdrometer calibration are much larger than what can be achieved with the combination of RCA and satellite comparisons. This simpler approach should therefore be used only in regions or time periods without TRMM or GPM coverage.

6. Integrated approach calibration framework

The RCA and the volume-matching technique are the elements that we introduced for our integrated approach SCAR to adjust the calibration of reflectivity. The self-consistency and birkbath techniques are all part of a broader framework for calibrating the differential reflectivity, as illustrated in Fig. 19.

To calibrate \(Z_h\), first the RCA is used, as it allows us to correct with great accuracy day-to-day variations of the radar calibration toward a predefined baseline. Then, the preferred way is to use the volume-matching technique to determine the absolute value of calibration of the RCA baseline. This is the SCAR framework. If satellite data are not available, then we use the self-consistency technique. Note that in this case, \(Z_h\) must already be calibrated, for example, using the birkbath technique.

The preferred way to calibrate \(Z_{\delta h}\) is to use the birkbath technique. If vertically pointing scans are not available, then the self-consistency technique can be used, provided that \(Z_h\) is calibrated. We propose using reflectivity comparison with a disdrometer as a last resort, since 1) it requires a disdrometer to be always present and (2) this technique has the highest uncertainty of all techniques considered here.

The reasons the volume-matching technique is the preferred way for our integrated approach are as
follows: 1) it works for single-polarization radar too and (2) the self-consistency relationship changes from radar to radar and therefore must be tuned using dedicated disdrometer observations.

The RCA technique is already in use at the Australia Bureau of Meteorology (BoM) for automatic monitoring of the calibration of 13 weather radars of the operational network (those recording uncorrected reflectivities). The SCAR integrated approach is also currently being ported at BoM for automatic comparison of the entire Australian radar network with GPM. At the time of writing, the Australian weather radar network is in the process of being upgraded to dual polarization. Plans to put disdrometers at some radar sites, which could allow the use of the self-consistency technique, are also in discussion.

7. Discussion and summary

In this paper an integrated approach for ground radar calibration, named SCAR, has been developed and tested using 17 years of tropical radar observations collected by the Darwin CPOL. The SCAR approach makes use of an improved version of the RCA technique to track calibration changes and a modified version of the satellite volume-matching technique from Warren et al. (2018) to derive the absolute calibration. We demonstrate that using this integrated approach, the absolute calibration can be achieved to within 1 dB and monitored to an accuracy better than 0.5 dB.

Using 17 years of CPOL-calibrated dual-polarization data and disdrometer observations, we have then studied the self-consistent calibration technique for this tropical location. We found that the CPOL-derived self-consistent relationship was very different from the midlatitude relationship derived at C band by Gourley et al. (2009). This important result highlights the fact that caution should be exercised before using relationships from the literature to observations from different geographical locations. Our recommendation is to use local disdrometer observations, combined with our integrated SCAR approach, to achieve an accurate calibration. The second important result is that the T-matrix estimates of the self-consistent relationship are very sensitive to the assumed standard deviation of the canting angle and drop-shape model. We found that only a few of the proposed drop-shape models and the standard deviation of the canting angle in the literature could reasonably reproduce our CPOL self-consistent relationship. The combination of the Brandes et al. (2002) drop-shape model and a standard deviation angle of 12° was found to provide the best match to the CPOL calibrated data,
with the Goddard et al. (1982) drop-shape model and a
10° standard deviation of canting angle a reasonably
good match too. Finally, we also showed that the self-
consistent relationships can be used to estimate the
calibration of $Z_{\text{dr}}$ to within about 0.2 dB, an accuracy
similar to that obtained with the traditional birdbath
technique, provided that $Z_{\text{dr}}$ is calibrated and $K_{\text{dp}}$ is
known. This result is particularly interesting for radars that
cannot perform vertical scans, such as the U.S. WSR-88D
of the NEXRAD network. For these radars the self-
consistency technique should be used to monitor $Z_{\text{dr}}$,
while the SCAR approach could be used to monitor $Z_{\text{dr}}$.

Acknowledgments. This work has been supported by
the U.S. Department of Energy’s Atmospheric System
Research program through Grant DE-SC0014063. The contribution
of Scott Collis through Argonne National Laboratory was supported by the U.S. Department of Energy, Office of Science, Office of Biological and Environmental Research, under Contract DE-AC02-
06CH11357. This work was partly supported by the Climate Model Development and Validation activity of the Department of Energy, Office of Science, Office of Biological and Environmental Research. We acknowledge
the contributions of Brad Atkinson, Ray Jones, and
Michael Whimpey in supporting the Darwin observatory
and data management. We also want to thank the authors of the ARM Py-ART library for its usefulness
in manipulating and processing radar data.

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