A ZDR Calibration Check using Hydrometeors in the Ice Phase

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Abstract

Monitoring the calibration of ZDR during real-time operations is now recognized as a necessary data-quality component in the use of dual-polarization radar for quantitative purposes, for example for QPE. Certain classes of hydrometeors have reasonably well-known ZDR signatures - rain drops at a specified reflectivity are an example. Similarly, a study of the particles in the ice phase of convective storms and MCSs during the PECAN field project revealed that the underlying distribution of ZDR appears predictable, and it may therefore be used as a check on ZDR calibration. The technique applied here uses the distribution of ZDR values in dry snow to estimate the bias of ZDR. Using the NCAR S-Pol radar allows us to check the results of the technique against those from other ZDR calibration methods, such as vertical pointing scanning technique. Furthermore, since the technique may be applied to radar volumes over a long period of time, it permits the study of variability in ZDR bias as the temperature at the radar site changes, which is useful since it is now known that ZDR bias has some dependence on temperature at the radar. In addition to the PECAN data sets, we have applied the method to the NCAR S-Pol radar data from the DYNAMO field project. The results are presented.

1 Introduction

This paper presents a method for assessing the measurement bias of ZDR, using the observations of radar returns from the dry snow regions of convective storms.

Gorgucci et al. (1999) discusses the technique for calibrating ZDR in light rain, by scanning the radar antenna through full rotations while vertical, since drops viewed from below are approximately circular and hence have a ZDR of 0. Rhzhkov et al. (2005) introduced the concept that some types of atmospheric scatterers are suitable for ZDR calibration, especially at high elevation angles, and that dry aggregated snow is particularly suitable. Richardson et al. (2017) shows that clear air Bragg scatter regions at S-band can be successfully identified and used for ZDR calibration – the ZDR in Bragg regions being intrinsically 0 dB.

Zittel et al. (2014) documents how the returns from both Bragg and snow regions are used for routine monitoring of the ZDR bias in the NEXRAD radar network. For the snow technique, the hydrometeor type is first identified using the NEXRAD Hydrometeor Classification Algorithm (HCA) (Park et al. 2009). A number of constraints are applied to ensure high data quality. The mean ZDR is then computed. It is known that the mean ZDR in snow is typically greater than 0 – in this method the intrinsic average value of ZDR in snow is determined to be 0.2 dB, by comparing with other methods. Therefore 0.2 dB is subtracted from the mean ZDR to estimate the ZDR bias.

The snow method described by Zittel et al. (2014) will be referred to as the ‘offset-mean’ method in this paper. The method described here is very similar to the offset-mean method, with the following differences: (a) the NCAR Particle ID (PID) algorithm is used to identify snow regions instead of the NEXRAD HCA, and (b) a selected percentile in the observed distribution of ZDR in the snow region is used instead of the offset mean of 0.2. We will refer to this modified method as the ‘percentile’ method.

Both the offset-mean and percentile methods are applied to data from 2 field projects in which the NCAR S-Pol radar participated: (a) the PECAN project in Kansas in 2015 and (b) the DYNAMO project in the Maldive Islands of the Indian Ocean in 2011. The PECAN project studied convective systems in the Midwest plains states of the US, with their largely continental air mass, while the air mass for the storms in DYNAMO was maritime in nature. This provides an opportunity to compare results from these quite different environments.

The NCAR S-Pol dual-polarization S-band radar has 2 major advantages over the NEXRAD radars with respect to research on ZDR monitoring and calibration: (a) it is an alternating mode radar, so that the ZDR bias may be determined using the cross-polar power method (Hubbert et al., 2002, Hubbert 2017), and (b) the antenna can be pointed vertically to allow for an independent ZDR check in light rain (Bringi and Chandrasekar, 2001).

The vertically pointing scanning method (Gorgucci, et al., 1999, Bringi and Chandrasekar, 2001) is used to provide a an estimate of the radar system ZDR bias, against which we can compare the results of offset-mean and percentile methods. Vertical pointing requires that the radar antenna be rotated 360 deg. while pointing vertically in precipitation. The theory is that the ZDR of precipitation particles when viewed from below and integrated over 360 deg. should be 0 dB.

The analysis in this paper shows that (a) the offset-mean and percentile methods produce similar results, (b) the percentile method produces results with somewhat less variability than the offset-mean method; (c) both the offset-mean and percentile methods require different tuning parameters when applying them to storms in different environments (DYNAMO vs PECAN).

2 Identifying the snow regions

Figure 1 shows the reflectivity in an RHI from the NCAR S-Pol radar during the PECAN project in Kansas in 2015. Figures 2 shows the ZDR for that same RHI.

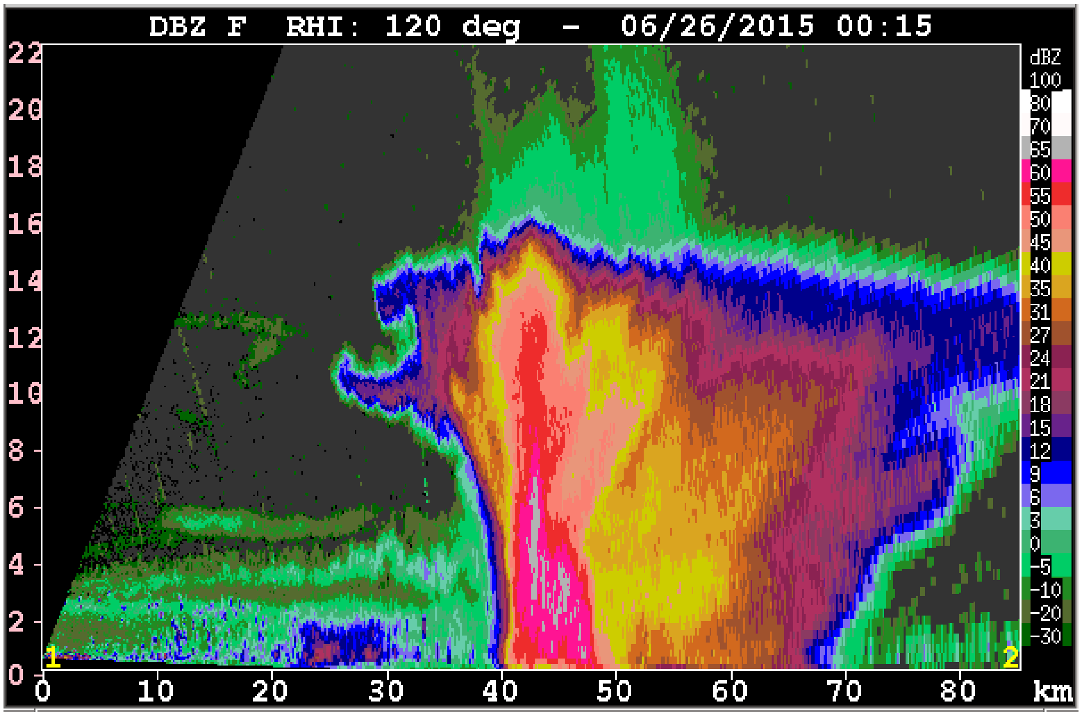

Figure 1. Reflectivity of RHI through a convective storm observed by the NCAR S-Pol radar at McCracken, Kansas during PECAN

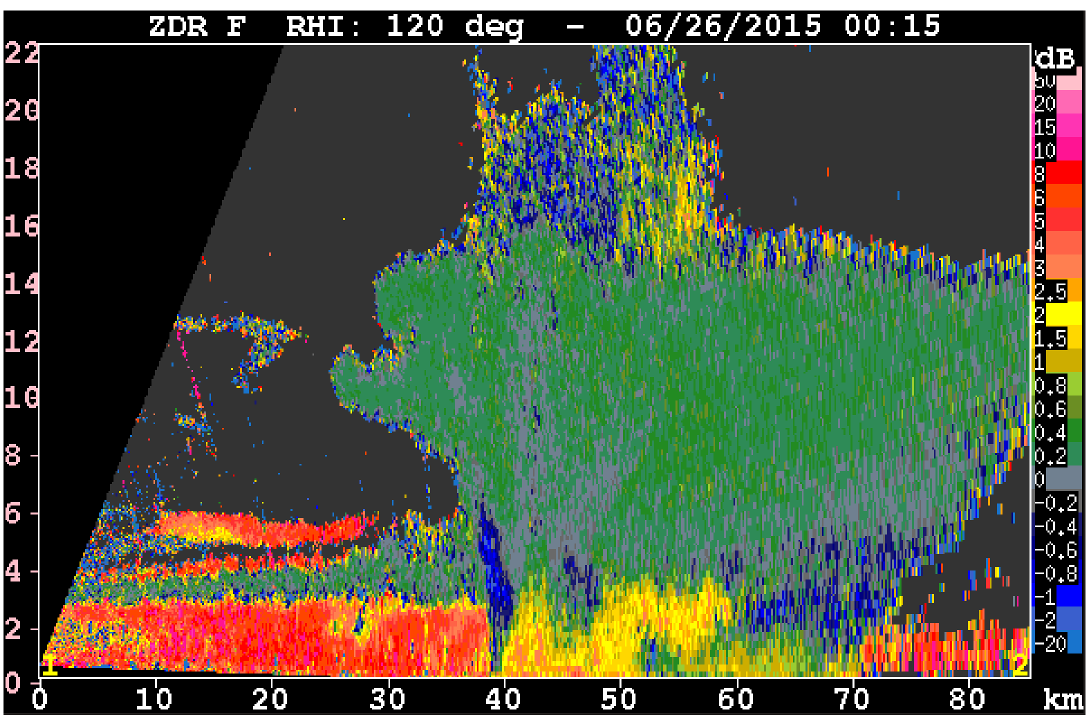

Figure 2. ZDR for RHI in figure 1

Figures 3 shows the results of running the NCAR Particle ID (PID) algorithm for this RHI (Vivek et al., 1999). The NCAR PID has 18 classifications, one of which (val = 10) is dry snow.

This is the category we use for selecting the ZDR values from which to compute the ZDR bias estimates in this paper.

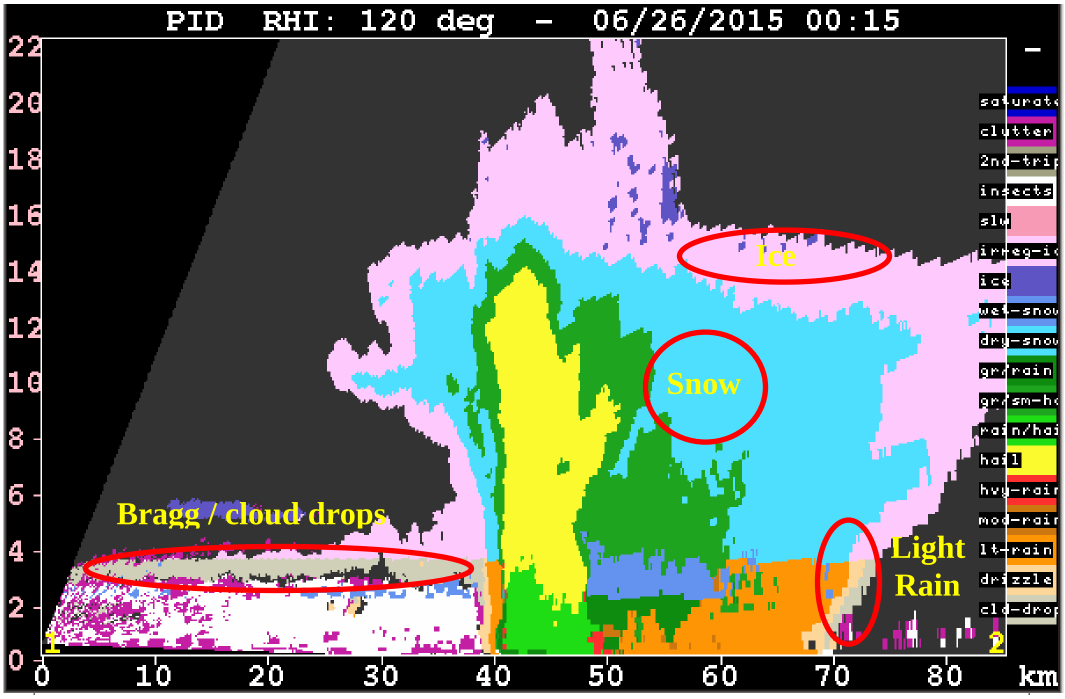

Figure 3. NCAR PID for RHI in figure 1

For echoes to be useful for determining the ZDR bias, they need to be regions that have a reliable and predictable ZDR distribution. Figure 3 shows some of the regions used by the methods mentioned in the introduction. Bragg echoes have ZDR values close to 0. In rain and dry snow, the mean ZDR values are above 0 by some small amount, around 0.2 dB, so these regions can be used by making a suitable correction.

We apply certain constraints when identifying the regions of dry snow. Table 1 below shows those constraints.

Field	**Constraint**
PID	Ice / dry snow
SNR	10 to 50 dB
Reflectivity	0 to 30 dB
Max Phidp accumulation	10 degrees
Temperature	-5 C to -50 C
KDP	< 0.6 deg/km
VEL	< -1.5 or > 1.5 (to avoid clutter contamination)
RHOHV (not noise corrected)	> 0.98

Field	**Constraint**
Elevation angle	< 25 degrees
Calibrated ZDR	< 0.75 dB
Min number of ice points in volume for valid analysis	1000

Table 1: constraints for locating regions of dry snow

3 The observed distribution of ZDR in dry snow - PECAN

For dry snow/aggregates, ZDR ranges from -1dB to 1.4dB (see Vivekanandan et. al. for details about NCAR's PID algorithm). Thus, in dry snow regions, ZDR will be negative in places and positive in others, but the distribution of ZDR values will span 0 dB. The region of dry snow must contain sufficient samples for the assumed ZDR distribution shape to be well approximated. The ZDR bias correction algorithm searches for regions in the radar echo in which the conditions in Table 1 apply.

Figure 4 shows the observed distribution histograms of ZDR in dry snow for the S-Pol observations from RHIs observed during the PECAN field project from 1 through 16 July 2015. S-Pol for PECAN was located near McCracken in Kansas, and many of the events were large-scale Mesoscale Convective Systems, in a largely continental air mass.

The blue lines show the fit for a normal distribution. The mean is 0.1 and the standard deviation is 0.13. The distribution is close to normal, though it is slightly skewed to the lower values.

Shown in red are the mean observed ZDR, and the (ZDR mean – 0.15) values, the offset of -0.15 being used by the offset-mean method to adjust the ZDR statistic downwards to match the vertical pointing results.

Also shown in black are the 5th, 15th and 25th percentiles. One of the main goals of this paper is to show that it is possible to select a percentile that effectively estimates the ZDR bias. For the PECAN data set, it turns out that the 15th percentile gives good results.

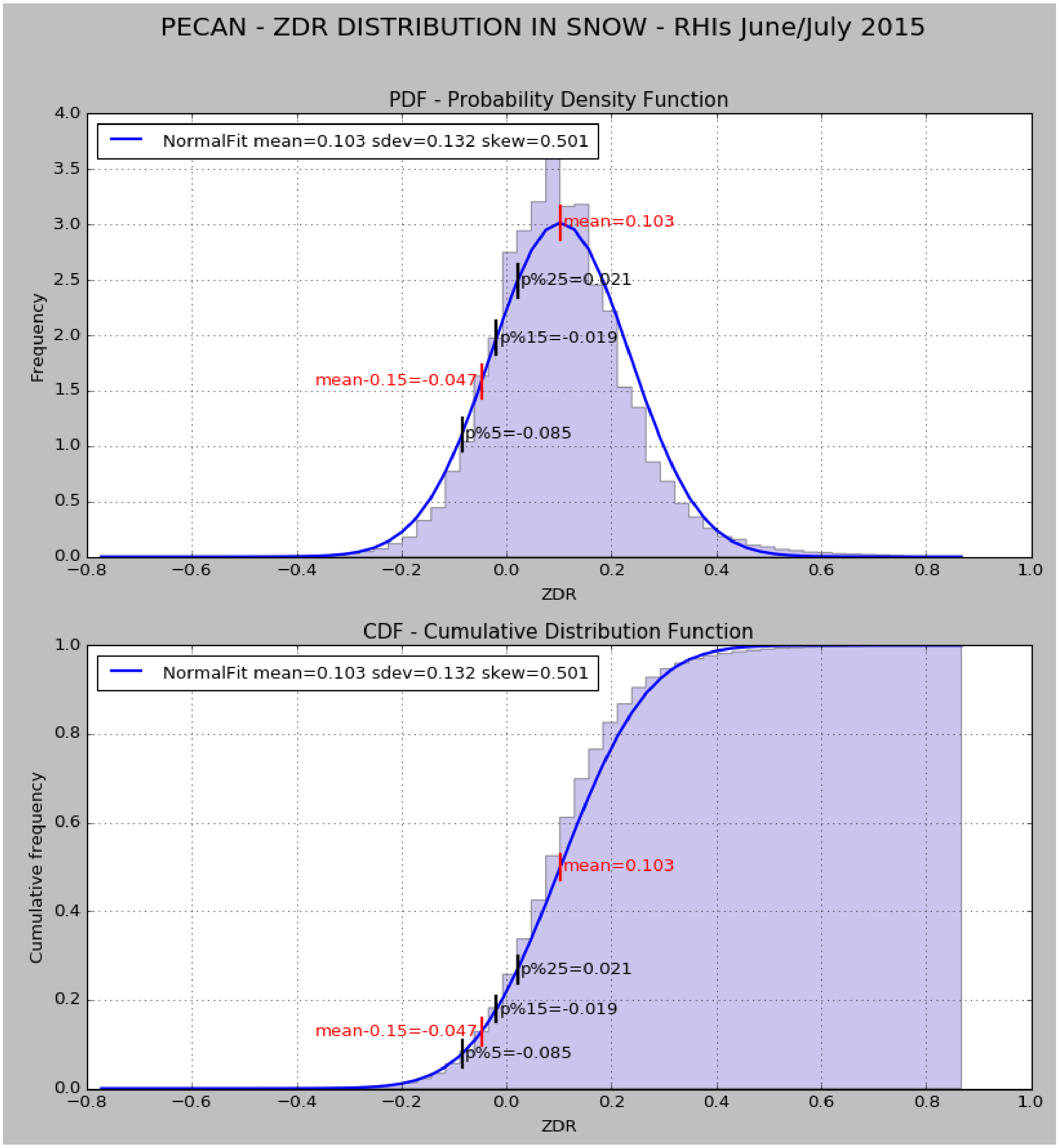

Figure 4. Observed distribution of ZDR in dry snow, RHIs from PECAN field project July 1 through July 16 2015

4 ZDR bias for PECAN

Through experimentation with the PECAN data it was found that the 15th percentile provides a good match between the observed distribution in snow and the vertical pointing results. Figure 5 shows the observed, and corrected, ZDR bias for the PECAN field project, for the time period from June 16 to July 16 2015. Shown in yellow are the 'truth' observations, from the vertical pointing scans. The blue icons show the ZDR values for the 15th percentile in the distribution. The upper plot is for the volume-by-volume analysis, and the lower plot shows the daily mean values. The red icons show the results after correcting for the bias and temperature (see section 6).

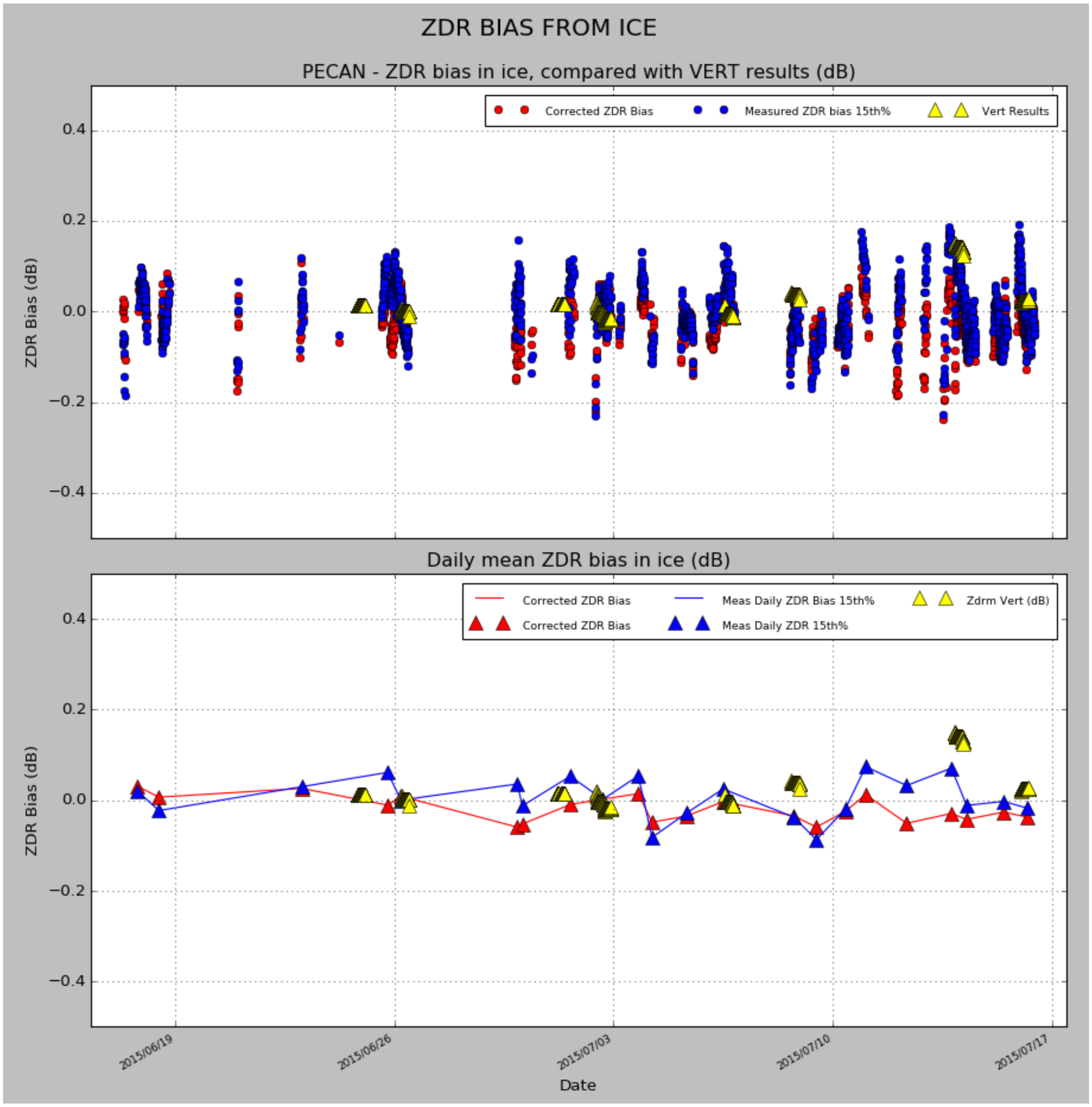

Figure 5. ZDR bias for PECAN, 15 June through 16 July, 2015
Blue: measured ZDR bias from 15th percentile in ZDR distribution
Yellow: vertical pointing results
Red: ZDR corrected for bias and temperature (see section 6).

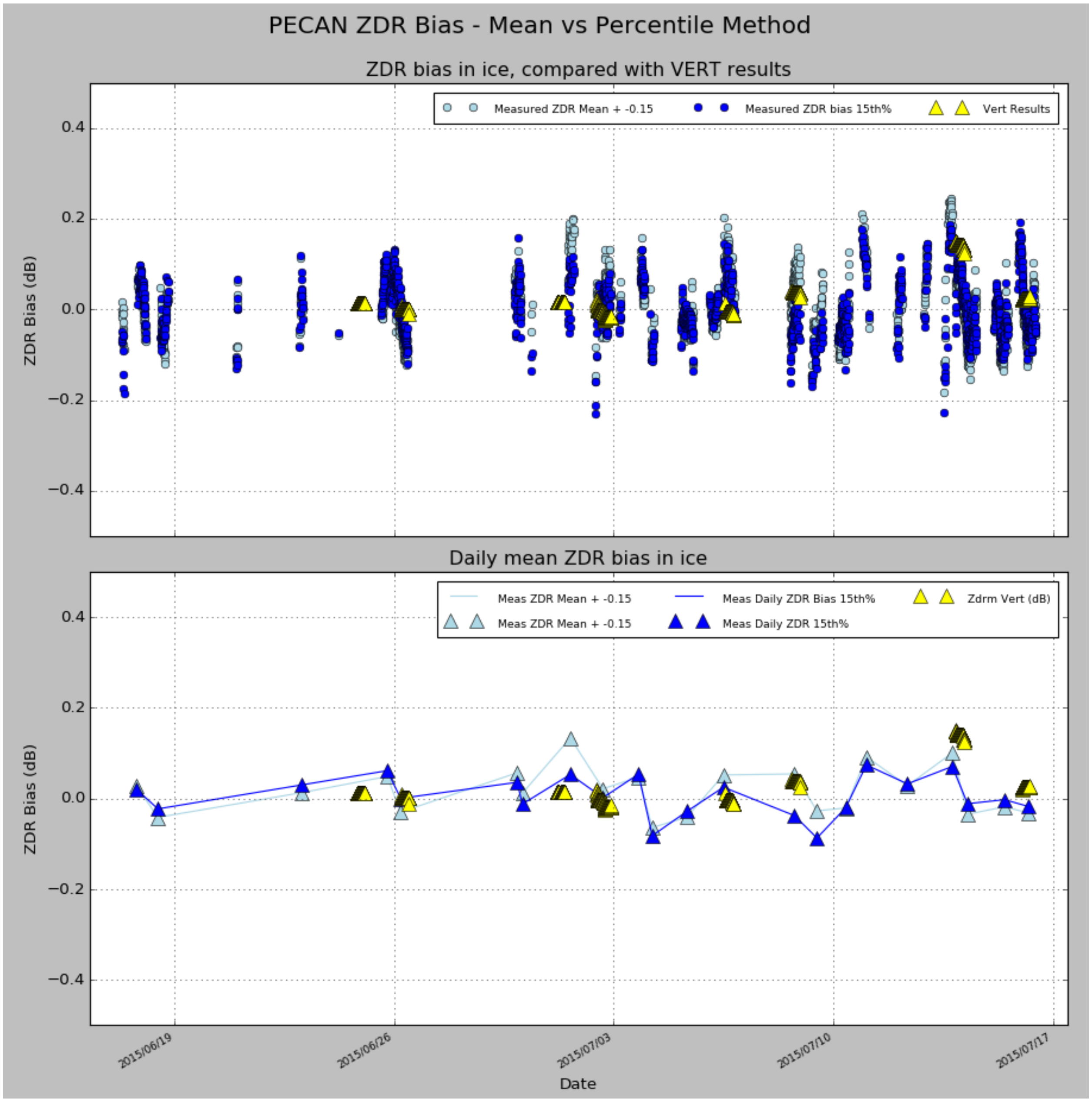

Figure 6. ZDR bias for PECAN, 15 June through 16 July, 2015
Blue: measured ZDR bias from 15th percentile in ZDR distribution
Light blue: mean – 0.15 dB

In order to compare the offset-mean and percentile methods, Figure 6 shows the 15th percentile of the ZDR distribution, in dark blue as in Figure 5, overlaid on the (mean – 0.15dB) values for the offset-mean method. The 0.15 dB offset was determined experimentally to give good agreement with the vertical pointing results. The vertical pointing results are shown in yellow.

Figure 6 shows that (a) the percentile and offset-mean methods produce similar results and (b) the percentile method appears to have less variability than the offset-mean method.

5 ZDR Bias for DYNAMO

Figure 7 shows the observed ZDR distribution for the DYNAMO field project, for all RHIs combined for the month of November 2011. Refer to Figure 4 for details.

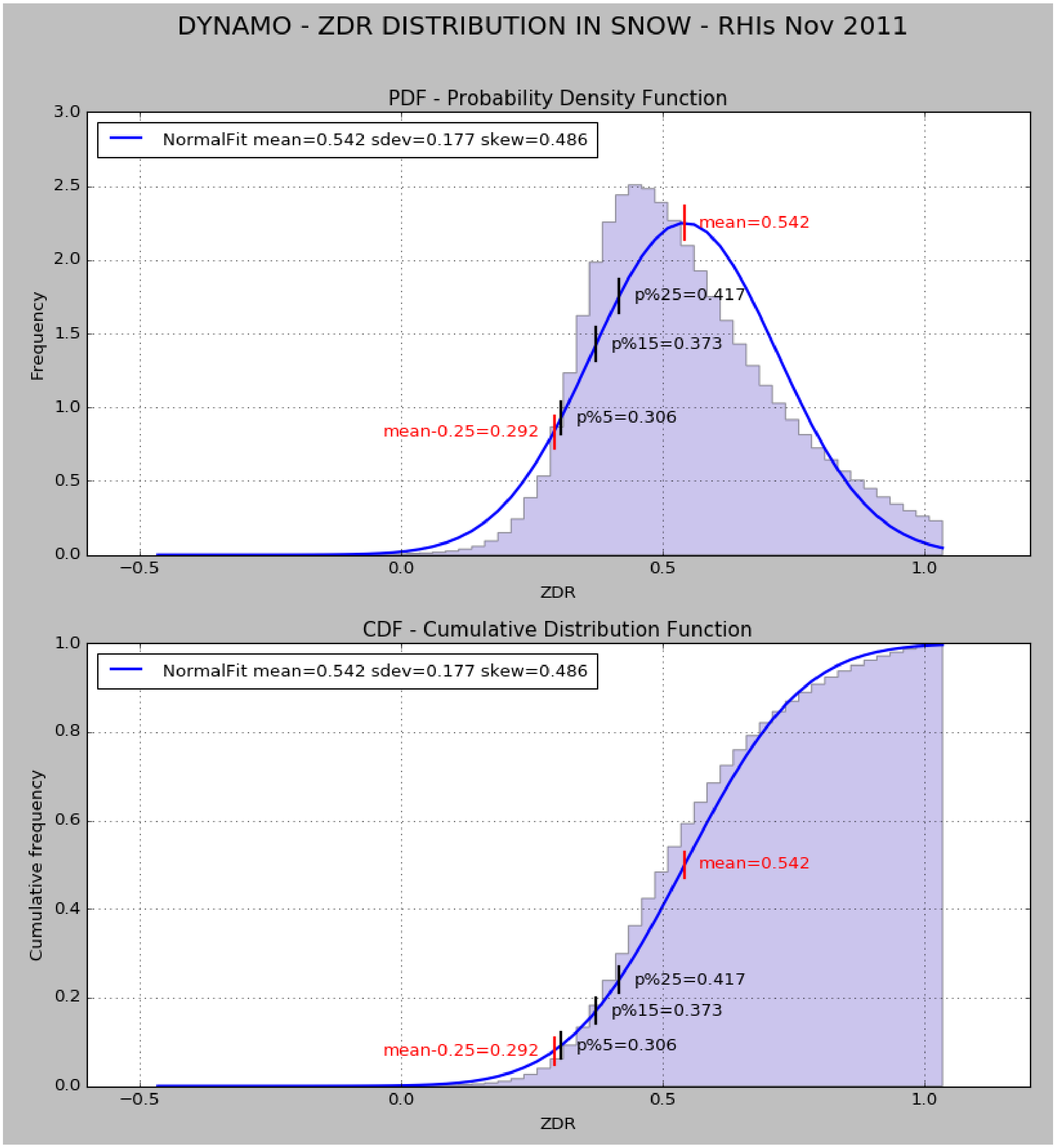

Figure 7. Observed distribution of ZDR in dry snow, RHIs from DYNAMO field project for the month of November 2011

The distribution is less close to normal that the distribution for PECAN.

It was found experimentally that a 5th percentile provided the best results for the percentile method, and an offset of -0.25 dB gave the best results for the offset-mean method. (These compare to the 15th percentile and offset of -0.15 dB for PECAN.) These differences indicate that the methods may require different tuning from one regional environment to another.

Figure 8 shows the results equivalent to Figure 5 above, for DYNAMO instead of PECAN. The red triangles in the lower panel show that the percentile method can correct the ZDR quite well, with little variability over time.

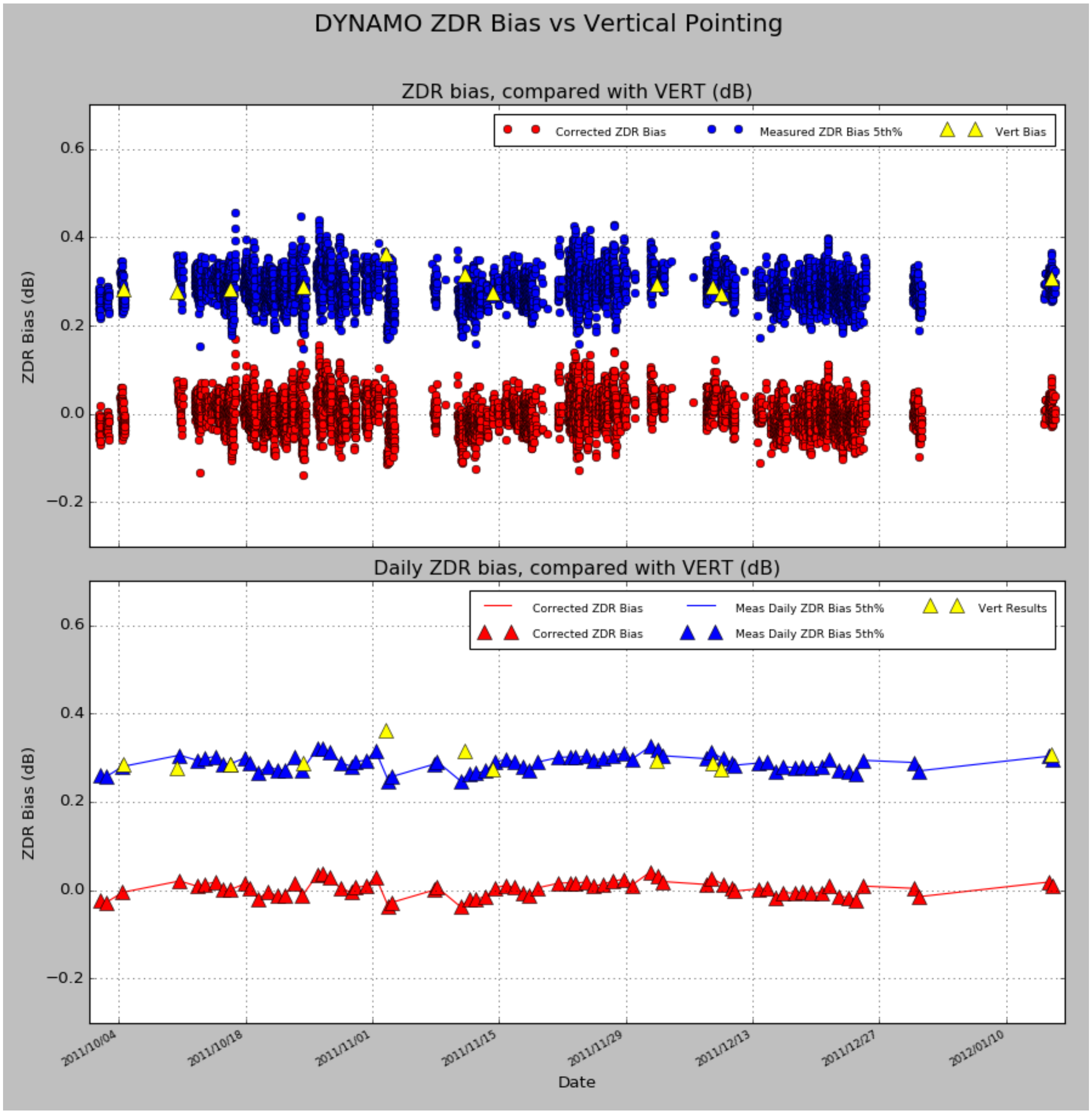

Figure 8. ZDR bias for DYNAMO, 1 October 2011 through 16 January 2012
Blue: measured ZDR bias from 5th percentile in the ZDR distribution
Yellow: vertical pointing results
Red: ZDR corrected for bias.

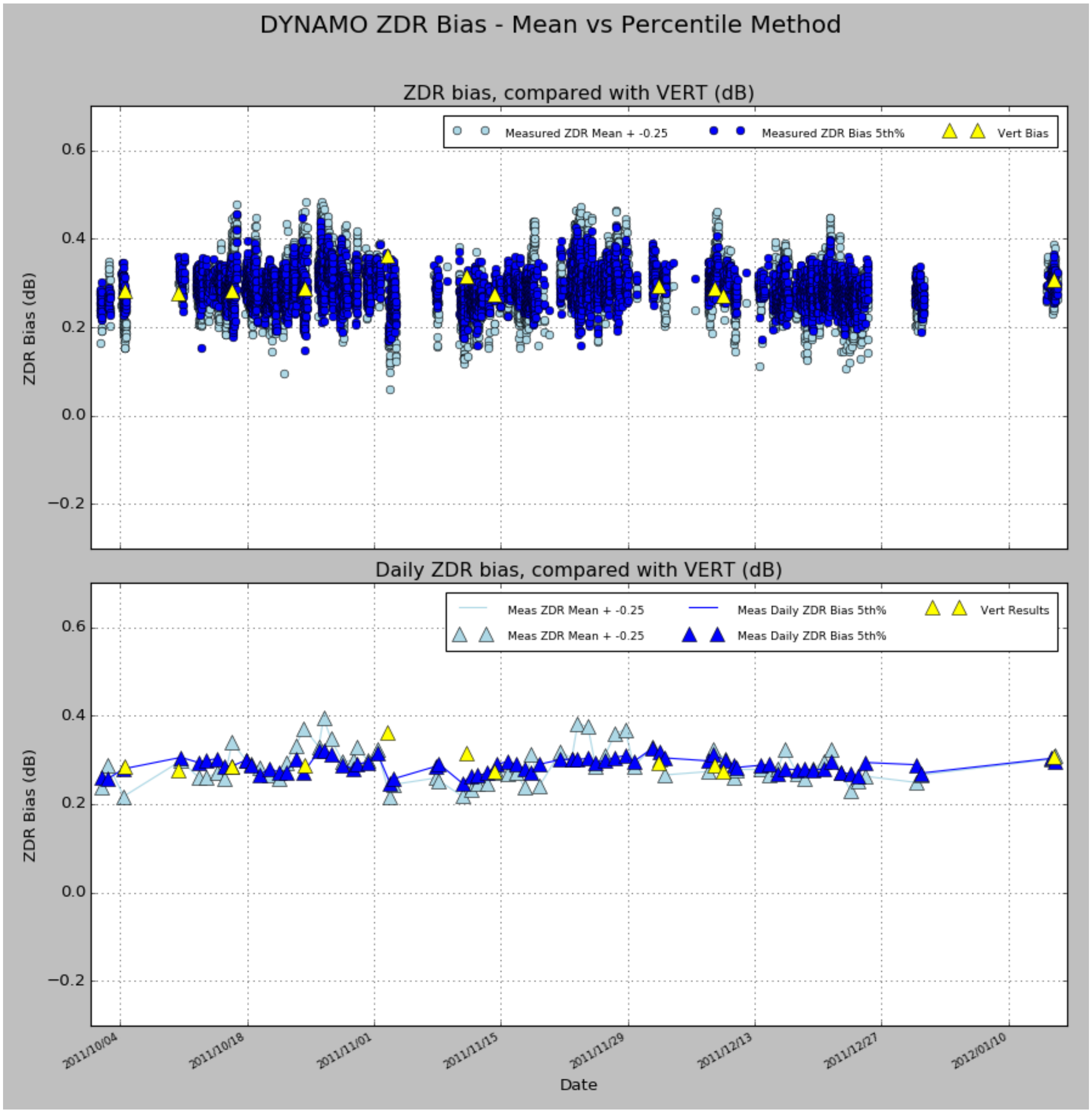

Figure 9. ZDR bias for DYNAMO, 1 October 2011 through 16 January 2012
Blue: measured ZDR bias from 5th percentile in ZDR distribution
Light blue: mean – 0.25 dB.
Yellow: vertically pointing results

For comparison of the offset-mean and percentile methods, Figure 9 shows the 5th percentile of the ZDR distribution, in dark blue as in Figure 8, overlaid on the (mean – 0.25dB) values for the offset-mean method in light blue.

Once again, it can be seen that these two methods are largely equivalent, though the percentile method exhibits lower spread than the offset-mean method.

6 The temperature dependence of measured ZDR

In the figures (5, 6, 8, 9) above, you will notice a quite significant spread in the volume-by-volume results in the top panel of the panel of the plots.

Figure 10 shows the ZDR 15th percentile results for PECAN, on a volume-by-volume basis, in the top panel, along with the observed site temperature in the lower panel.

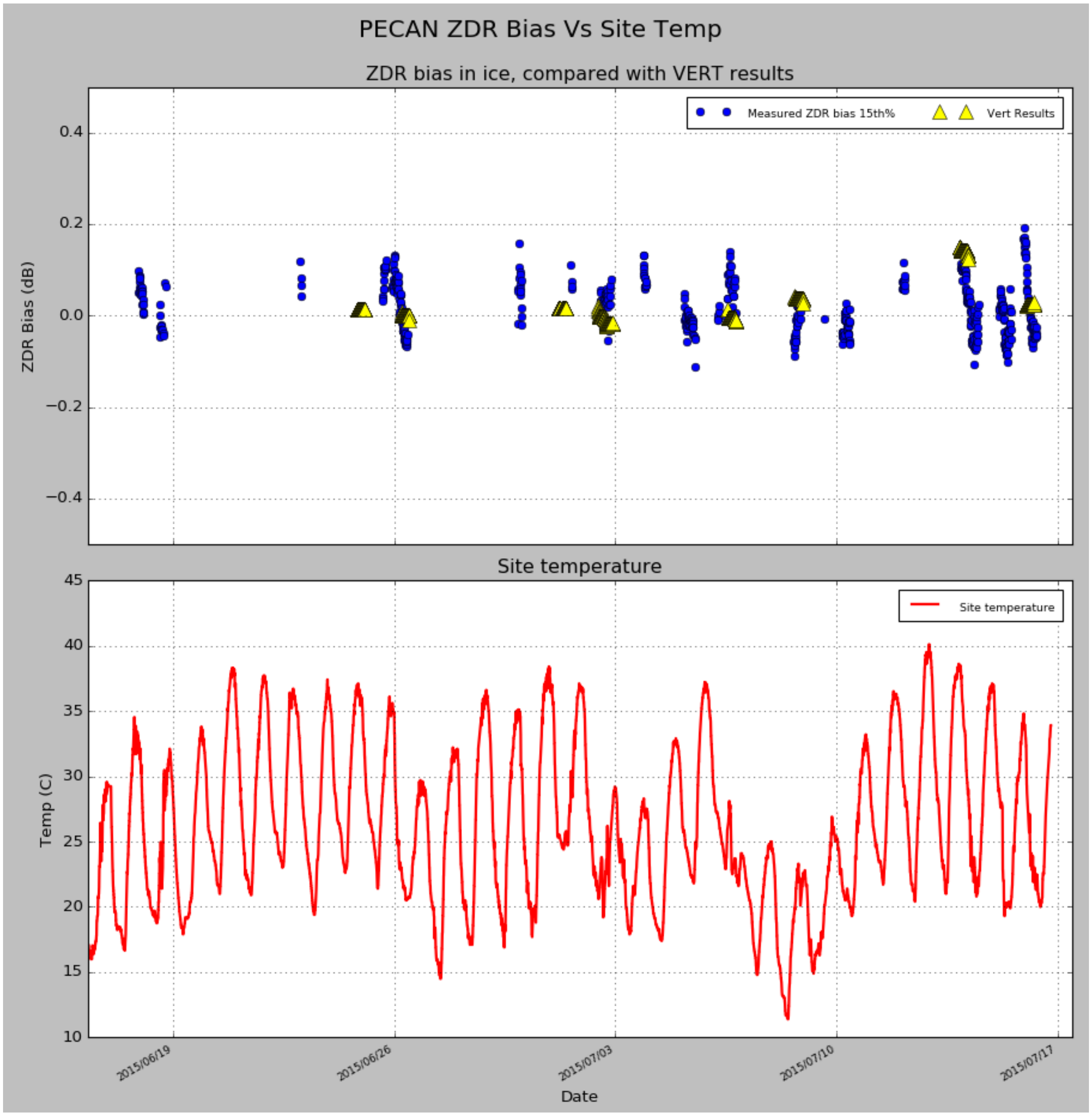

Figure 10. Blue: volume-by volume ZDR 15th percentile
Yellow: vertically pointing results
Red: observed site temperature, showing the diurnal cycle.

During the course of this study, and other analyses of S-Pol ZDR data, it was noted that the observed ZDR bias is a function of the diurnal variation of temperature at the radar. Since S-Pol has no radome, the site temperaure is a good proxy for the dish temperature.

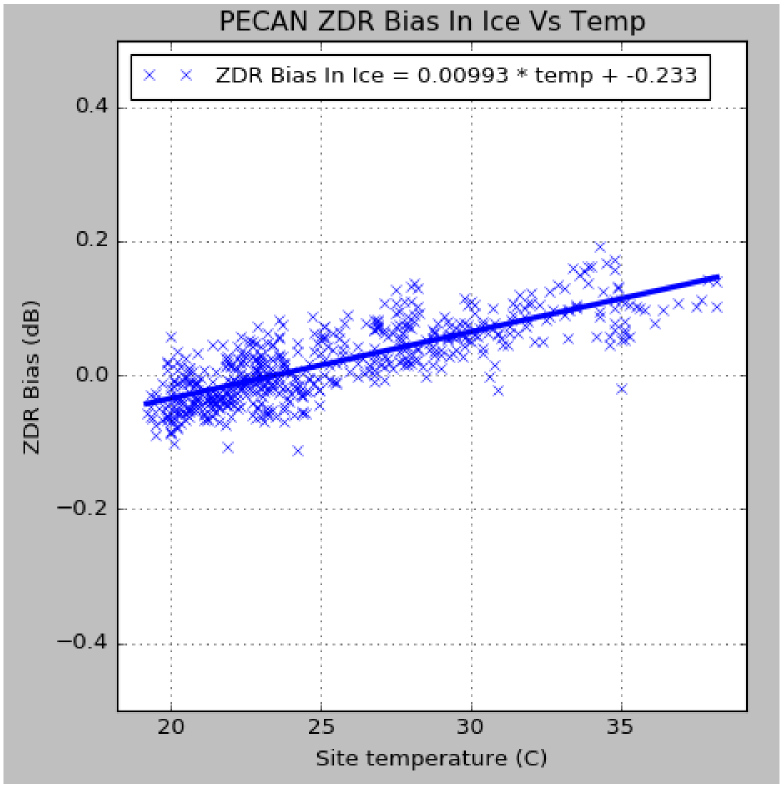

Figure 11. Regresssion plot of observed ZDR bias (from the 15th percentile) vs the site temperature, for PECAN from June 16 to July 16 2015.

Figure 11 shows the observed dependence of ZDR bias on temperature for PECAN. A similar relationship was found when applying the cross-polar power method (Hubbert et al. 2003, Hubbert 2017). Using this relationship, the observed ZDR values for PECAN were corrected for both ZDR bias and temperature. The red line in the lower panel of Figure 5 shows the corrected results on a day-by-day basis.

7 Summary and Conclusions

The offset-mean method for ZDR bias estimation in dry snow, as described by Zittel et al. (2014), was evaluated, along with a modified version of this method that uses percentile values in the observed distribution of ZDR, instead of the adjusted mean. Both of these methods were run on data from the PECAN and DYNAMO field projects.

The two methods were shown to produce similar results. However, it does appear that the results from the percentile method have less variability over time than those from the offset-mean method. This is likely because the percentile results are less sensitive to a few large values in the distribution which might bias the mean in some circumstances.

Table 2 below shows the offsets and percentile values for each of the two methods, as determined from the results of the two field projects. The fact that the parameters vary significantly from one environment to another suggests that care must be taken in applying these methods in an operational setting.

Project	**PECAN**	**DYNAMO**
Environment	USA Mid-west plains	Maritime
ZDR mean offset for ZDR of 0	-0.15 dB	-0.25 dB
Percentile for ZDR of 0	15th	5th

Table 2: parameters determined for each field project

Future work will include:

- the use of a 3-parameter function to describe the observed ZDR distribution, in order to more accurately capture the shape;
- testing of the method on surveillance scans with an elevation angle of around 60 degrees, to test the hypothesis put forward by Ryzhkov et al. that snow observed at high elevation angles should have an intrinsic ZDR of close to 0. If this works, it may prove useful for the NEXRAD radars which cannot point vertically, but which can reach an elevation angle of 60 degrees.

8 Acknowledgements

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