WR Data Quality Monitoring using Operational Observations

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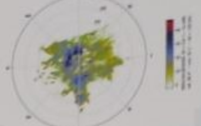


eywords

"Weather Radar Data Quality"

Abstract

We introduce a method for assessing the Weather Radar (WR) data quality using operational observations and demonstrate examples of its use. We present the WR data quality assessment of the Vaisala WRM200 research WR at Kerava near Helsinki before and after the recent Magnetron replacement, finishing with conclusions and an outlook.

Motivation

Monitoring data quality of WR observations crucial for:

- Assuring quality of direct observables and derived products.
- Informing subsequent use of observables and products.
  - Example: weight to observations assimilated into NWP models.

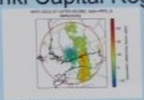
Supports adaptive approach to WR maintenance.

- Adapt maintenance activities to state of individual WRs.
  - Replaces fixed schedule.
- Supported by Artificial Intelligence / Machine Learning.
  - Provide points of intervention.

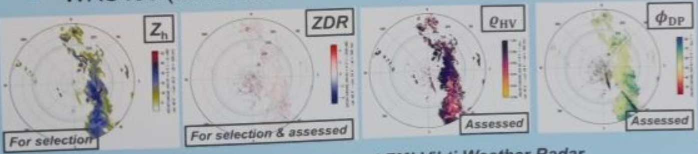
Example

Method implemented in Python code using PyART[1].

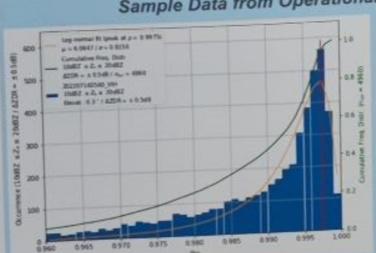
Observations from Vaisala Research WRs and one operational FMI WR located in wider Helsinki Capital Region:



- WRM200 (Magnetron C-band) at Kerava & Vihti (FMI Op.);
- WRS300 (Solid State Power Amplifier C-band) at Kumpula;
- WRS400 (Solid State Power Amplifier X-band) at Vaisala HQ.

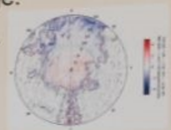


Sample Data from Operational FMI Vihti Weather Radar



Method

1. Identify Melting Layer Height (MLH) and its range.
2. Select data from ranges closer than MHL range.
3. Mask data for Z_h, e.g. 10 dBZ ≤ Z_h ≤ 20 dBZ.
4. Mask data for Z_{DR}, e.g. $|Z_{DR}| \le 0.5$.
5. Calculate statistics for observables and fit theoretical functions.



For **correlation coefficient** ρ_{HV}:

$$f(x) = \frac{a}{\sqrt{2\pi}\cdot\sigma\cdot x}\cdot e^{-\frac{(\log(x)-\mu)^2}{2\sigma^2}}$$

with $x = 1 - \rho_{HV}$.

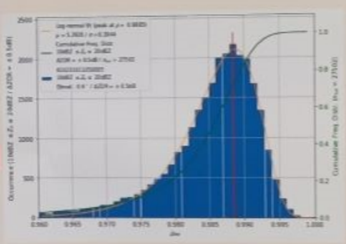
For **differential phase** Φ_{DP}:

$$f(x) = a\cdot(s\cdot x)^{\mu}\cdot e^{-\lambda}$$

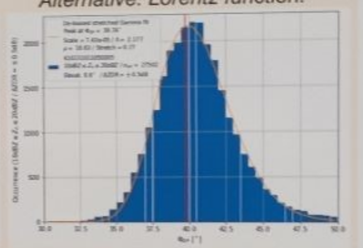
with $x = \Phi_{DP} - {}^{max}\Phi_{DP} + 10°$.

- ${}^{max}\Phi_{DP}$: distribution maximum;
- a: amplitude factor;
- s: stretch factor;
- μ and λ: shape parameters.

Alternative: Lorentz function.



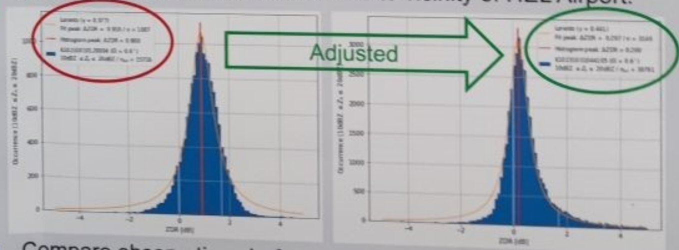
Reversed log-normal fit for ρ_{HV}



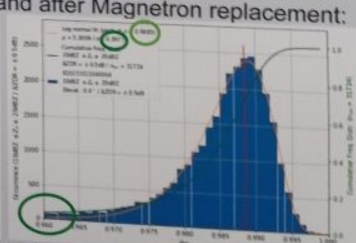
Stretched Γ fit for Φ_{DP}

Magnetron Replacement at Kerava WR

- Research WR at Kerava recently updated with new Magnetron.
- Birdbath calibration not allowed due to vicinity of HEL Airport.



- Compare observations before and after Magnetron replacement:



- Distribution of correlation coefficient ϱ_{HV} clearly improved.
  - More narrow, low contribution of region $\varrho_{HV} < 0.96$.
  - Some outstanding optimisation regarding peak location.

Conclusions and Outlook

- Quality assessment method demonstrated with Python code.
  - Clear indication of difference in WR data quality.
    - Allows comparison and assessment.
  - Allows continuously monitoring and adjusting ZDR calibration.
- Extension of statistics over multiple scans.
  - Larger sample size allows more stringent restrictions on data.
- Option to develop automated tool.
  - Ingest auxiliary external observations.
  - Apply WR-internal observations or products.
    - Hydroclass, polarimetric observables.
- Allows adaptive calibration and maintenance.
  - Utilise output to schedule activities flexibly.

Acknowledgment

[1]Py-ART, the Python ARM Radar Toolkit (JJ Helmus and SM Collis, JORS 2016, doi: 10.5334/jors.119), has been used to create the intercomparison plots.

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