Weather Radar Data Quality Monitoring using Operational Observations

Dirk Klugmann[1] , Jordan Santillo[1], Robinson Wallace[2], Juha Salmivaara[1], Pekka Puhakka[1]
[1]*Vaisala Oyj, Vantaa, Finland*
[2]*Vaisala Inc, Boulder, CO, USA*

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Contents

Introduction / Motivation

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Monitoring data quality of Weather Radar (WR) observations crucial for:

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

Monitoring data quality of WR observations supports adaptive approach to WR maintenance.

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

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Introduction / Motivation

- Looking for assessment method (nearly) exclusively using Weather Radar Observations.
  - Alternative: reference sensors, e.g. Vaisala FD70 (Marbouti et al.).
- Avoid interruption of operational observations.
  - Birdbath scan, external WR calibration, …
- Observations from Vaisala Research WRs located in Helsinki Capital Region:
  - WRM200 at Kerava;
  - WRS300 at Kumpula;
  - WRS400 at Vaisala HQ.
- Observations from FMI operational WRM200 WR at Vihti.
- Examples created with Python code.

Method

Method – Observables Quality Evaluation

1. Identify Melting Layer Height (MLH) and its range.
   - Using external information (e.g. Radiosonde) or Radar observations.
2. Select data from ranges closer than MLH range.
3. Mask data for Z_h, e.g.10 dBZ $\leq Z_h \leq$ 20 dBZ.
   - Other ranges for Z_h possible, e.g. 20 dBZ $\leq Z_h \leq$ 40 dBZ.
4. Mask data for Z_{DR}, e.g. $|Z_{DR}| \leq 0.5$.
   - More stringent masking for Z_{DR} possible, e.g. $|Z_{DR}| \leq 0.1$, if enough observations available – requirement: meaningful statistics!
5. Calculate statistics for observables and fit theoretical functions.

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Method – Fit Functions

- Fit function for **correlation coefficient** ρ_{HV} takes the form:

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

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

- Fit function of **differential phase** Φ_{DP} takes the form:

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

  with $x = \Phi_{DP} - {}^{max}\Phi_{DP} + 10°$, where ${}^{max}\Phi_{DP}$ denotes distribution's maximum, a is an amplitude factor, s a stretch factor, μ and λ are shape parameters.

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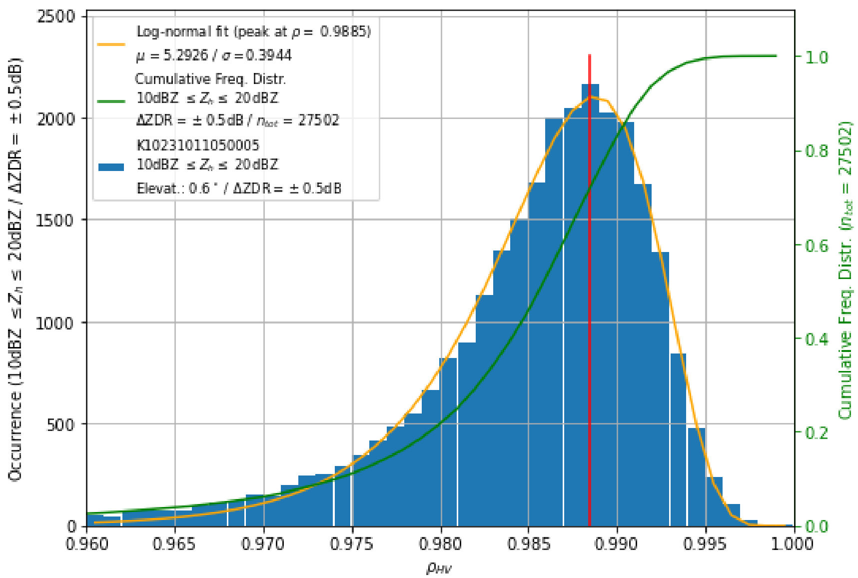
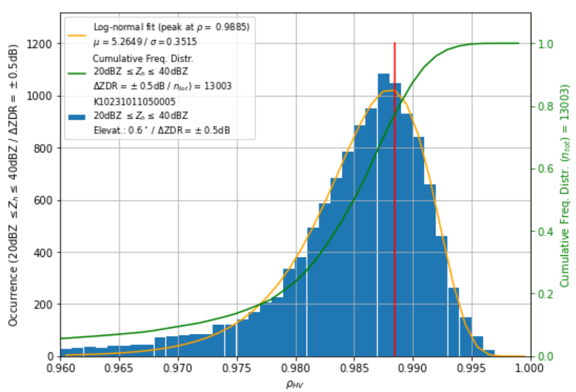
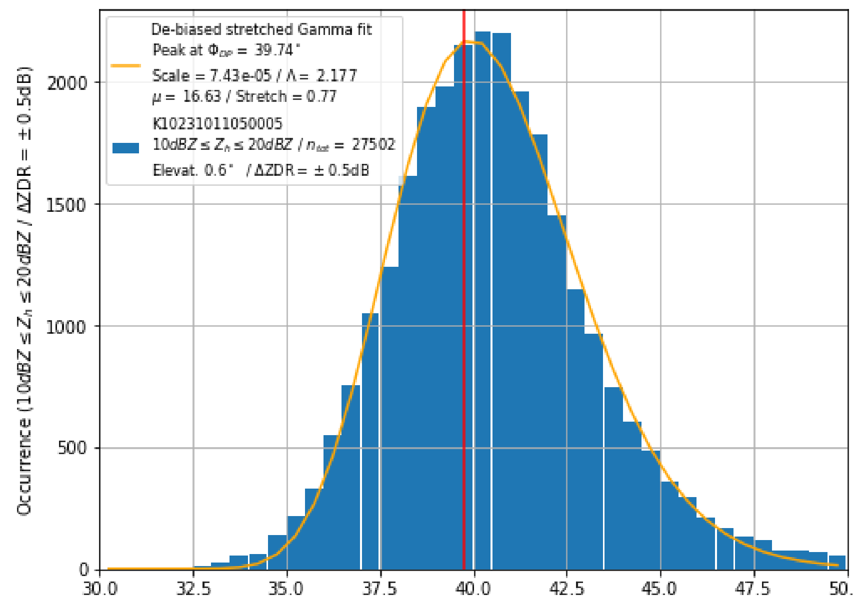
Method – Fit Functions

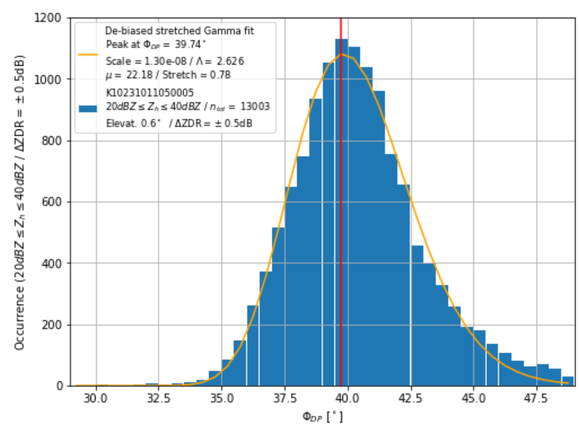
Reversed log-normal fit for ρ_{HV}





Stretched Γ fit for Φ_{DP}





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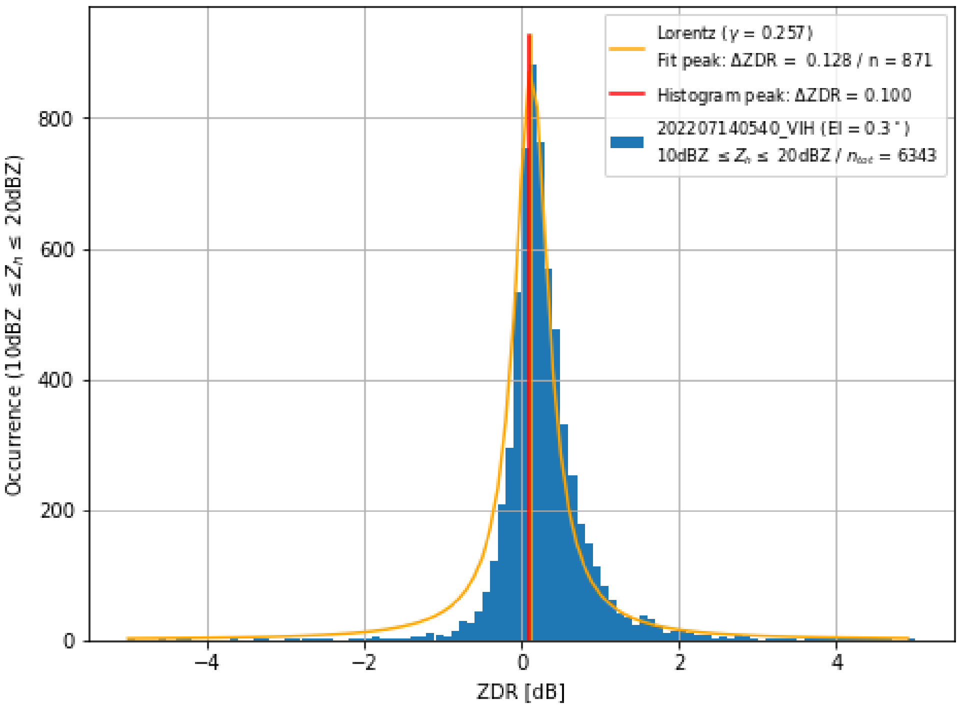
- Alternative fit function for **differential phase Φ_{DP}**:

$$f(x) = \frac{\pi \cdot \gamma}{1 + \left(\frac{x - x_0}{\gamma}\right)^2}$$

(Lorentz function).

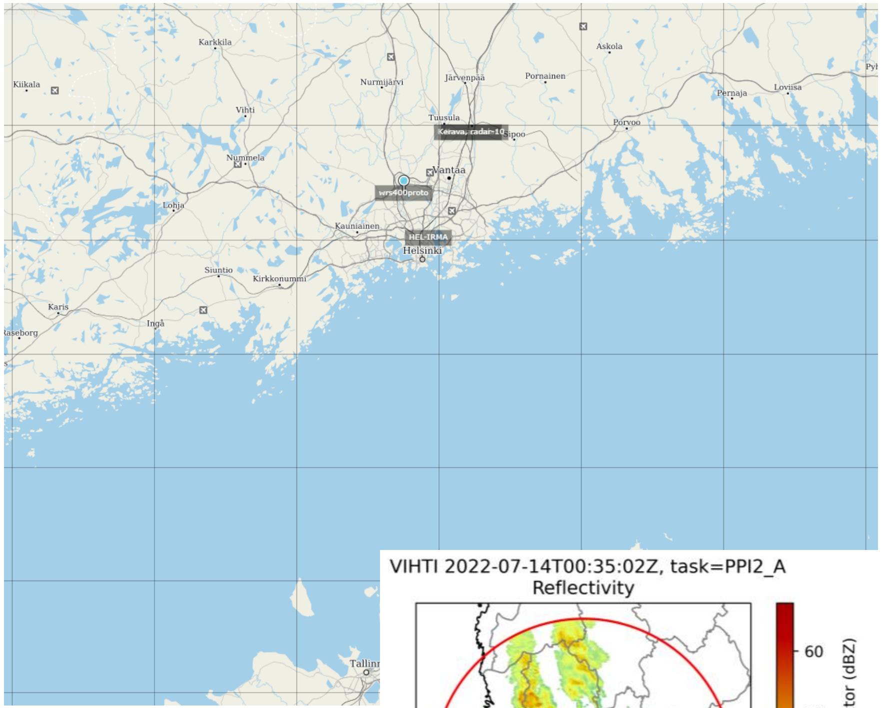
- Also used for fitting distributions of *ZDR*.

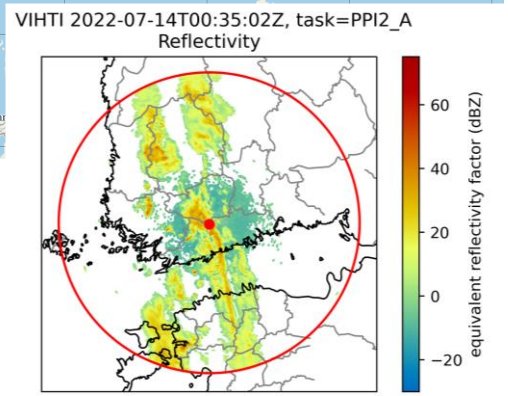


Examples

Examples

- Method implemented in Python code using PyART[1].
- Observations from Vaisala Research WRs and one operational FMI WR in wider Helsinki Capital Region.
  - WRM200 at Kerava & Vihti (FMI operational);
  - WRS300 at Kumpula;
  - WRS400 at Vaisala HQ.
  - All WRs within 50km.





[1]*JJ Helmus and SM Collis, JORS 2016, doi: 10.5334/jors.119*

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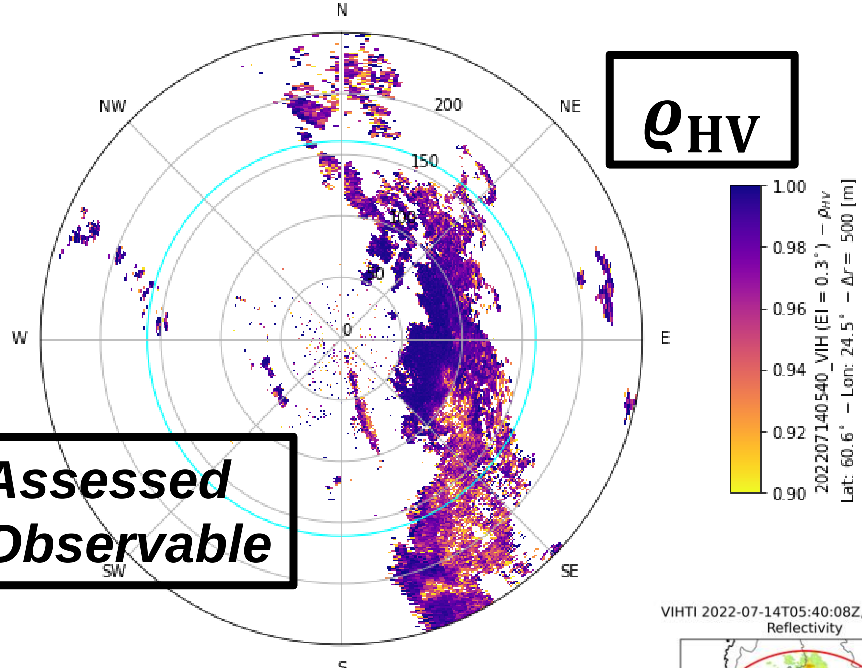
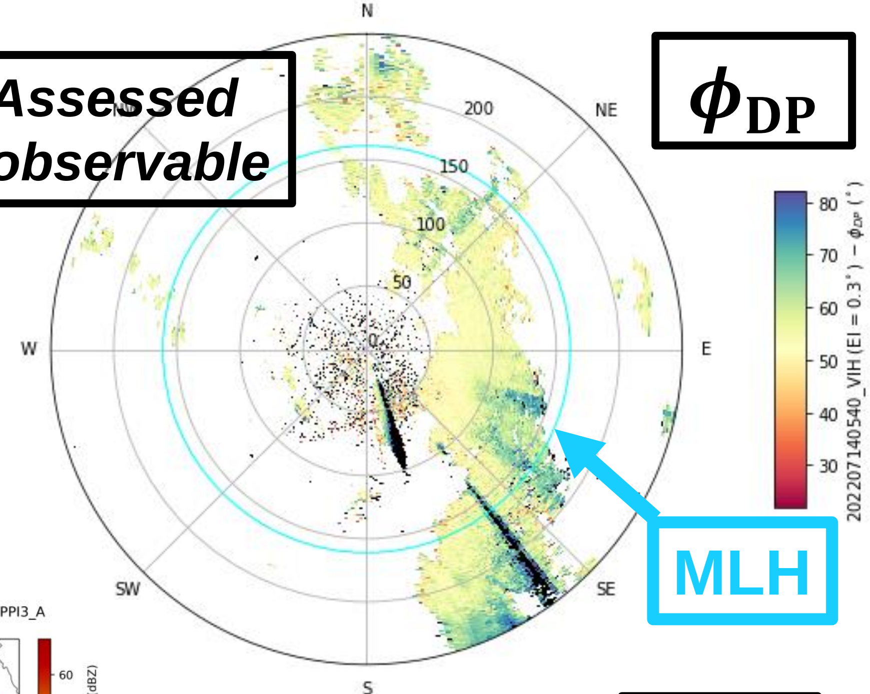
Examples – Input Observations



ϱ_{HV}

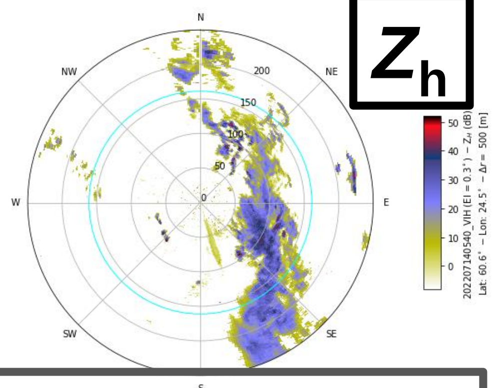
Assessed Observable



Assessed observable

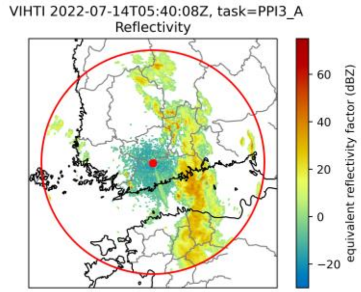
ϕ_{DP}

MLH

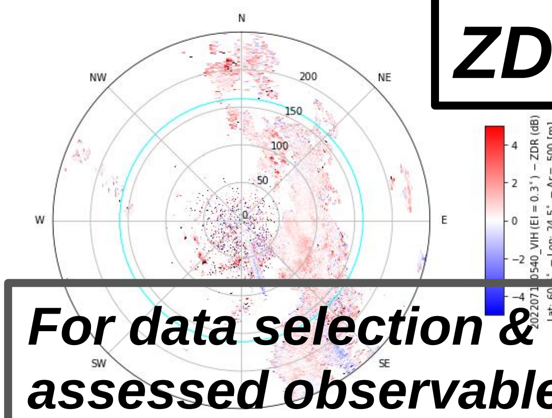


Z_h

For data selection



Sample Data from Operational FMI Vihti Weather Radar



ZDR

For data selection & assessed observable

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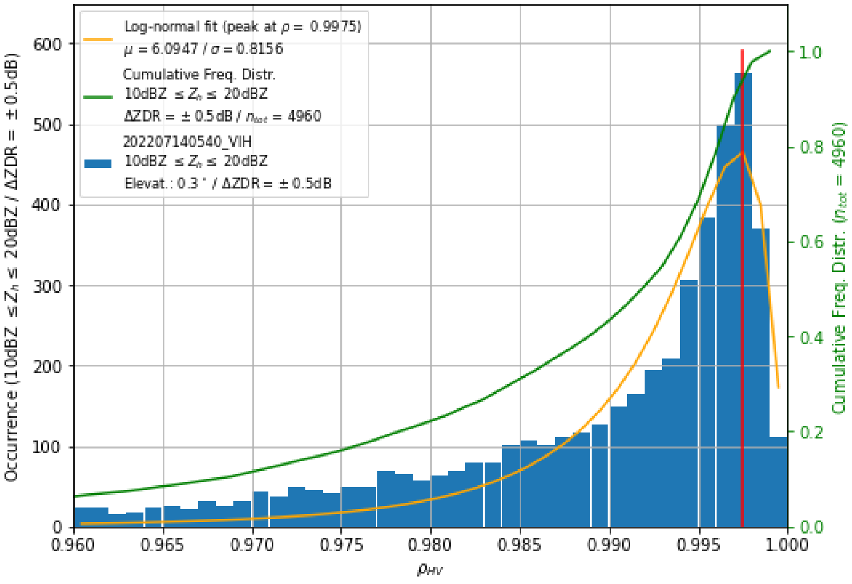
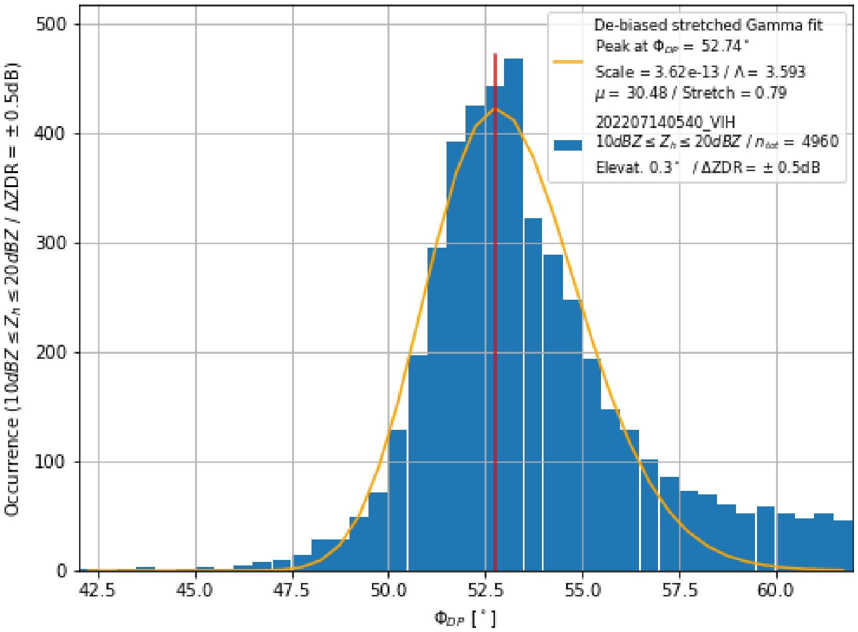
Example – Assessment FMI Vihti WR

Reversed log-normal fit for ρ_{HV}

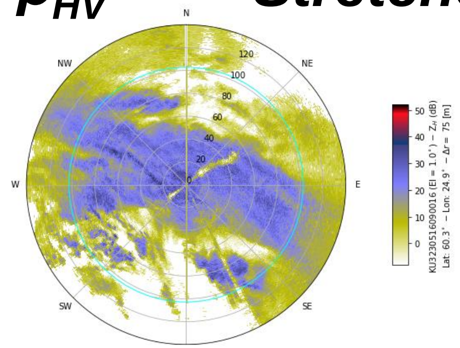


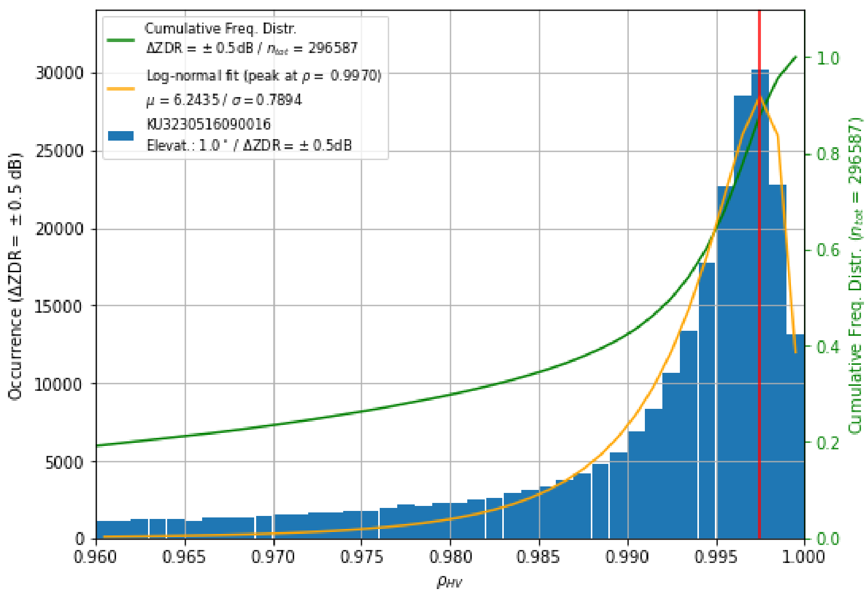
Stretched Γ fit for Φ_{DP}

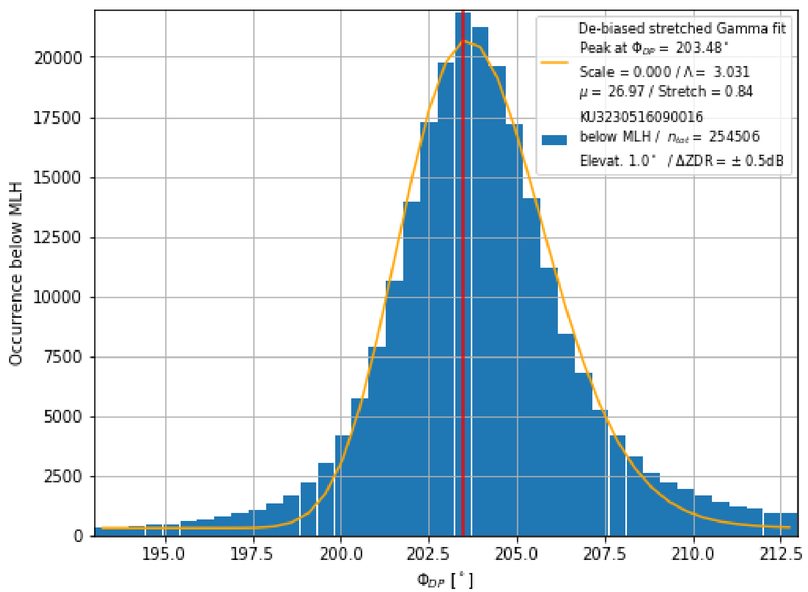


Example – Assessment Kumpula WR

Reversed log-normal fit for ρ_{HV} ***Stretched Γ fit for Φ_{DP}***







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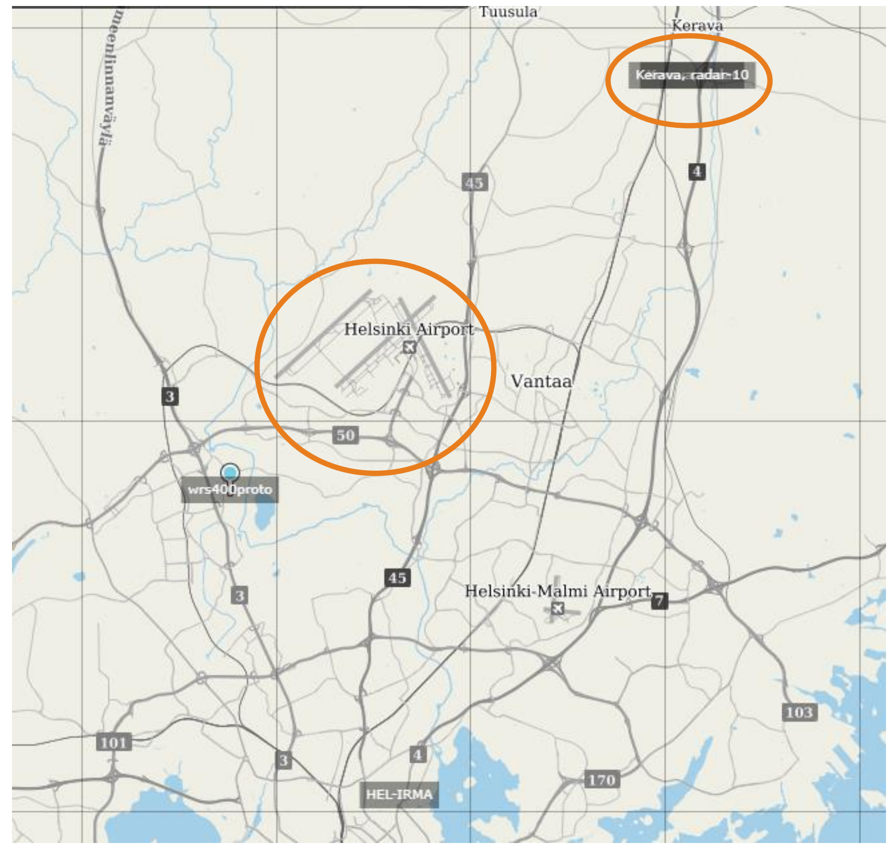
Kerava WRM200 Research WR Data Quality

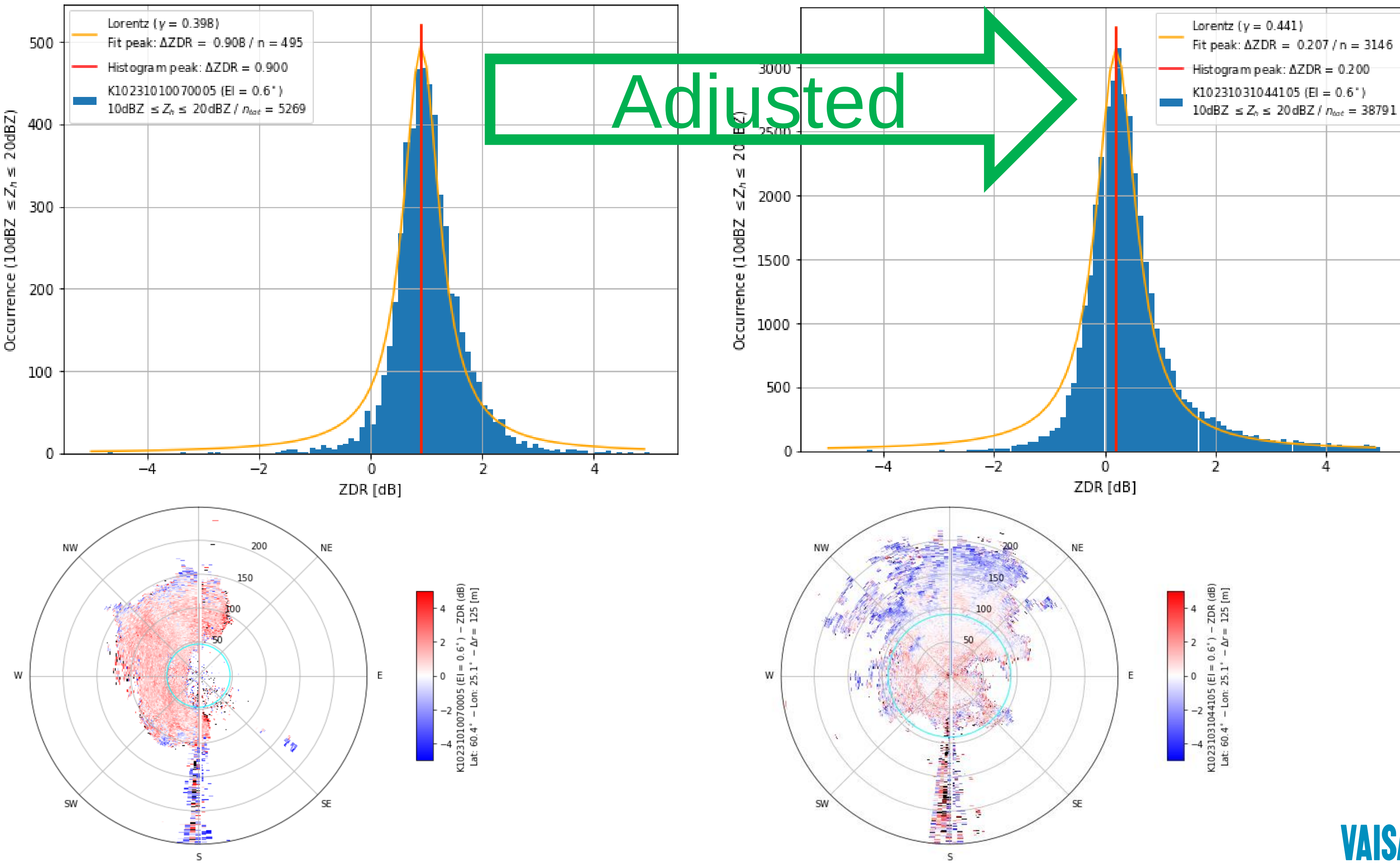
ZDR Calibration

ZDR Calibration

- Research WR at Kerava recently updated with new Magnetron.
  - Modern up-to-date design.
- Birdbath calibration not allowed due to vicinity of HEL Airport.
  - Necessitates alternative ZDR calibration approach.



ZDR Calibration



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WR Data Quality

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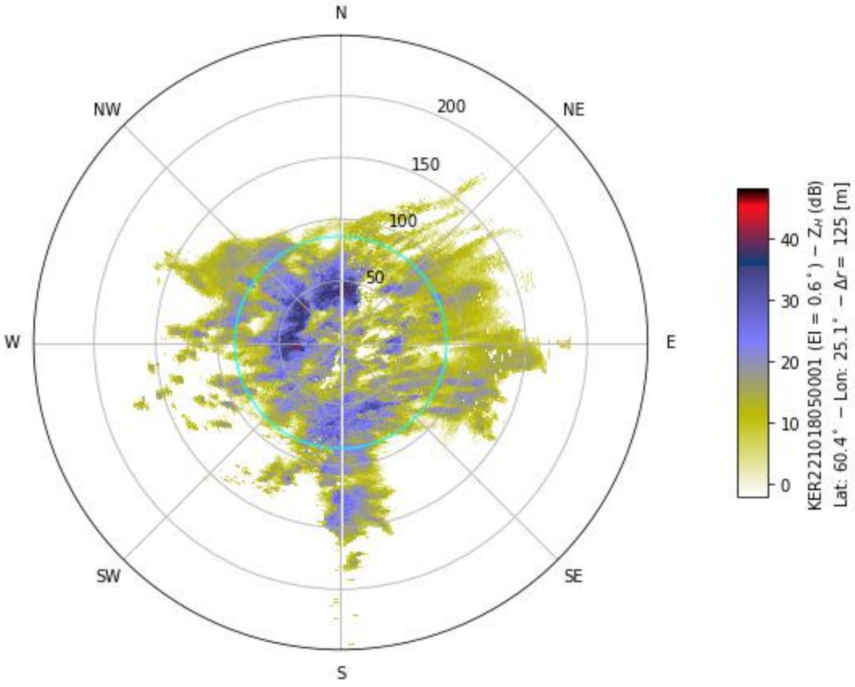
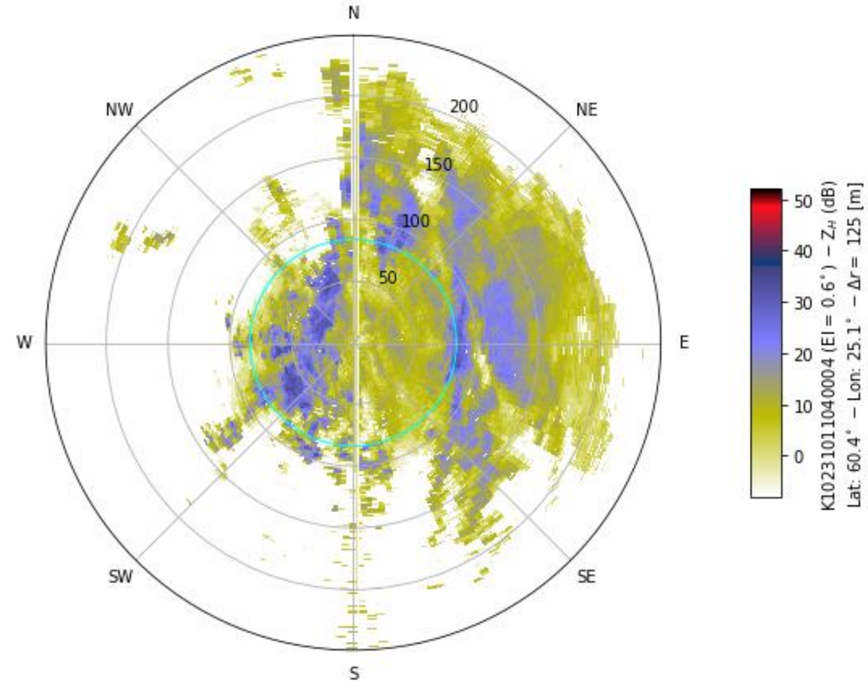
WR Data Quality

Old Magnetron – 18/10/2022   New Magnetron – 11/10/2023





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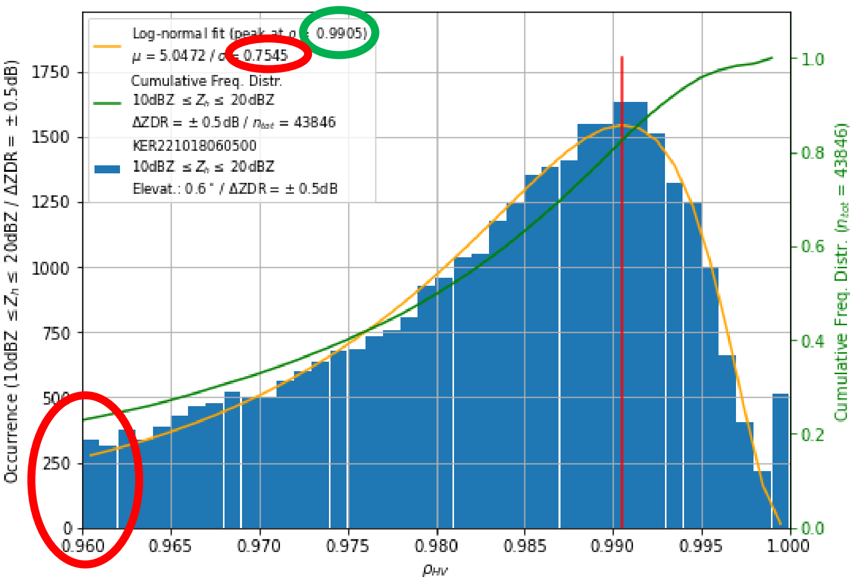
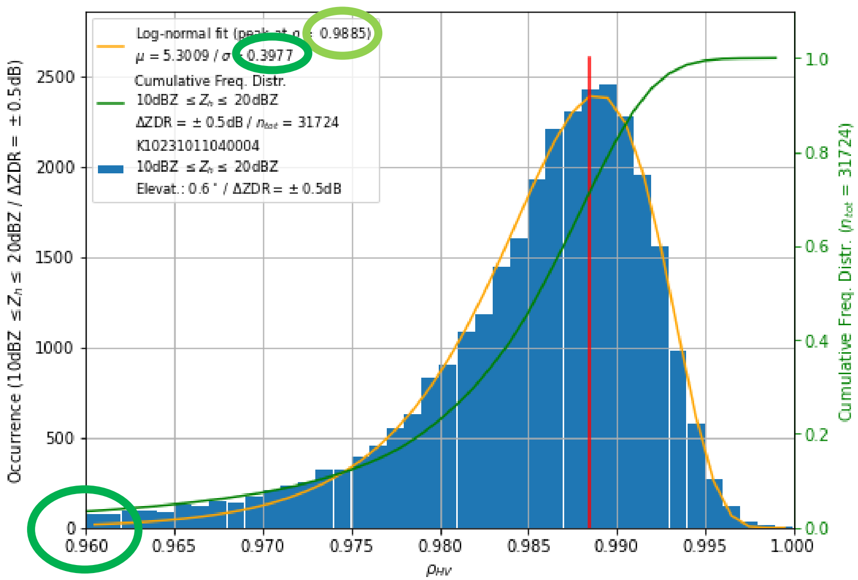
WR Data Quality – ϱ_{HV}

Old Magnetron – 18/10/2022 **New Magnetron – 11/10/2023**

Clear improvement of distribution width with new magnetron.





Distribution more narrow, contribution of $\varrho_{\mathrm{HV}} < 0.96$ much lower.
Optimisation ongoing to push new magnetron peak to $\varrho_{\mathrm{HV}} > 0.99$.

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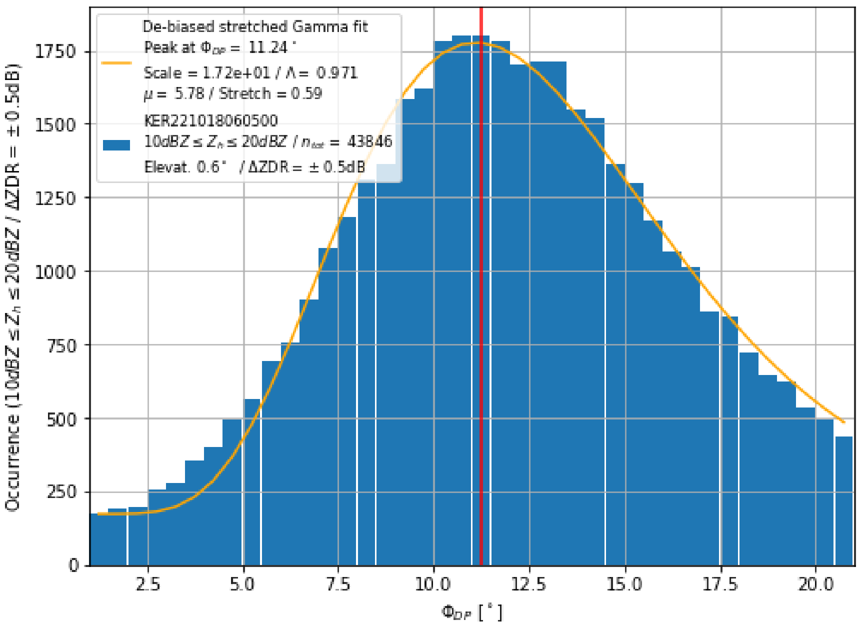
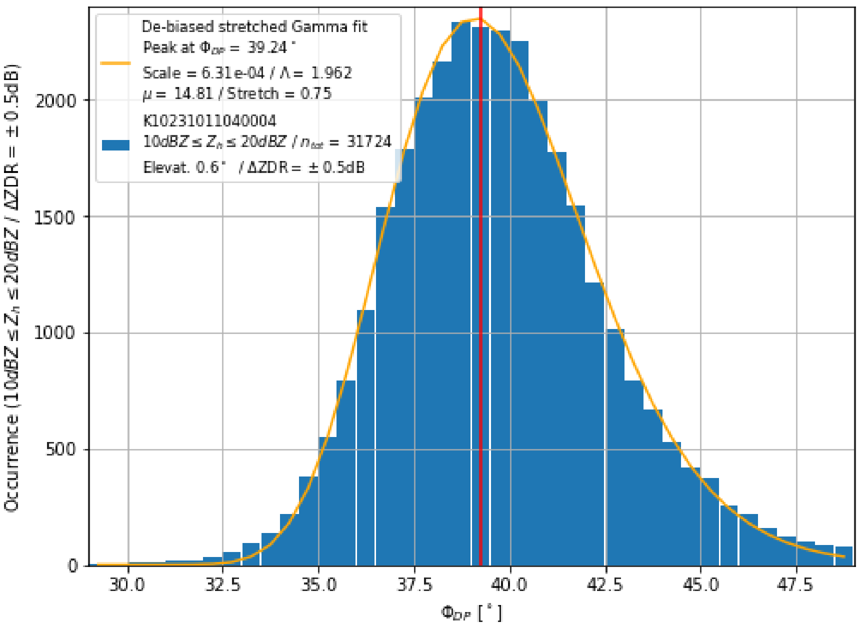
WR Data Quality – ϕ_{DP}

Old Magnetron – 18/10/2022 New Magnetron – 11/10/2023

Clear improvement of distribution width with new magnetron.





Distribution for $\phi_{\mathrm{DP}} > {}^{\max}\phi_{\mathrm{DP}}$ might be influenced by weather.
Distribution for $\phi_{\mathrm{DP}} < {}^{\max}\phi_{\mathrm{DP}}$ strictly due to Magnetron quality.

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Conclusions

Conclusions

- Quality assessment method using operational observations demonstrated with Python code.
- Useful for monitoring / adjusting ZDR calibration.
  - Peak of ZDR distribution for moderate values of Z_h good indicator for offset.
  - Improvement of ZDR calibration.
- Clear indication of difference in WR data quality.
- Multiple indicators for ϱ_HV.
  - Width of distribution;
  - Cumulative contribution of $\varrho_\mathrm{HV} < 0.96$.
- Indication for ϕ_DP: width of distribution.
  - Indicated by stretch factor and Λ parameter.

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Outlook

Outlook

- Extention over multiple scans.
  - Larger sample size allows more stringent restrictions on data.
- Option to develop automated tool.
  - Ingest external observations.
  - Apply WR-internal observations or products.
    - Hydroclass, polarimetric observables.
- Adaptive calibration and maintenance.
  - Utilise output to schedule activities flexibly.

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Summary

Summary

- Quality assessment method using operational observations 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.
  - Might be supported by AI / ML.

Thank you for your attention!

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