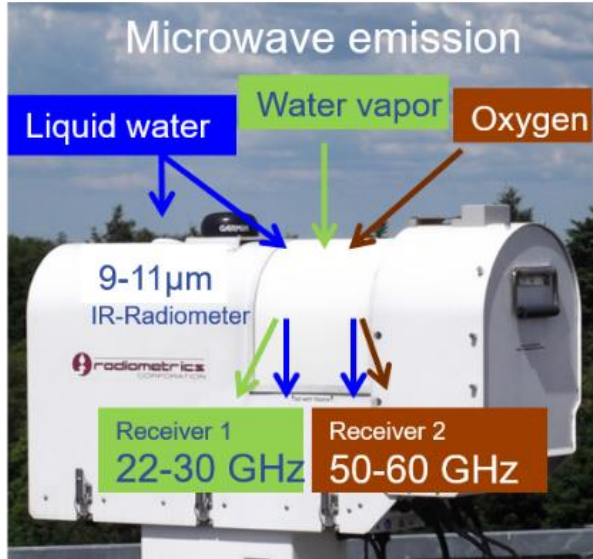


Cloud detection and quality checks for stand alone ground based microwave radiometer

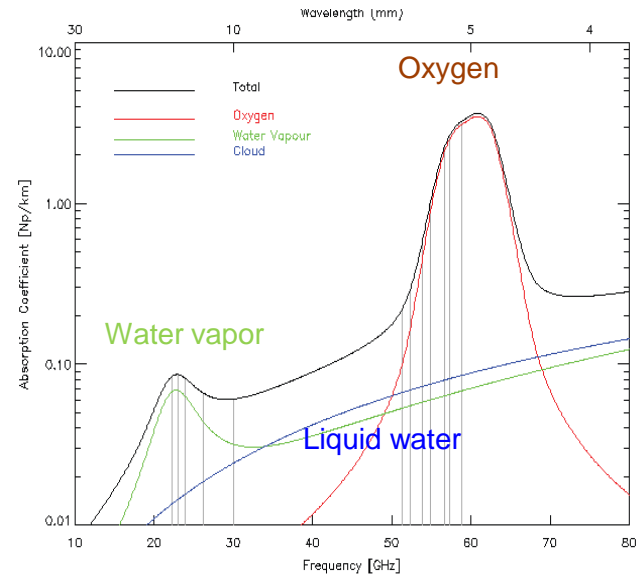
Moritz Löffler

BMD Seminar

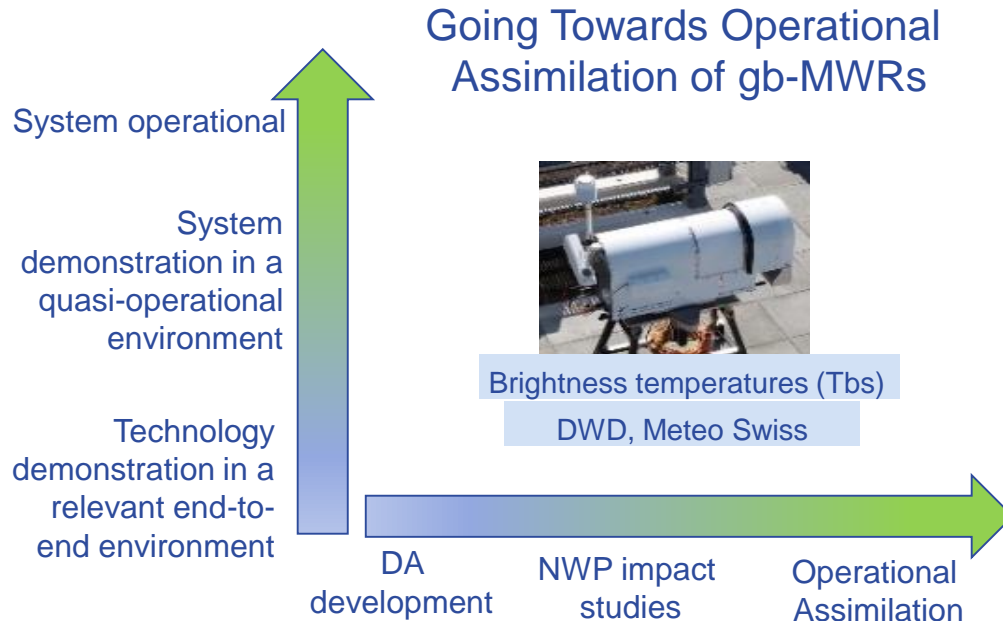
14.6.2022



- LV1: Brightness temperatures (T_b)
- LV2: Temperature and water vapor profile
Liquid water path (LWP)



Microwave Radiometers in Weather Prediction



EUMETNET's

E-PROFILE activities until 2023

Rolf Rüfenacht, Alexander Haefele, Simone Bircher and the E-PROFILE team

realisation of a MWR network

Technical centre in Jülich/Cologne



standard operating procedures/quality assurance for ACTRIS sites



Pilotsite for ground based remote sensing. Developing a concept for operational deployment

Data for Assimilation

Data Aquisition



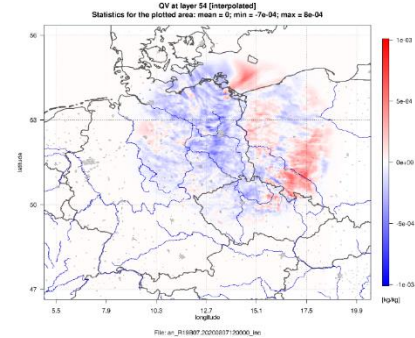
Quality Checks

Liquid Water
Cloud in Sky

Clear-Sky or
Ice Cloud only

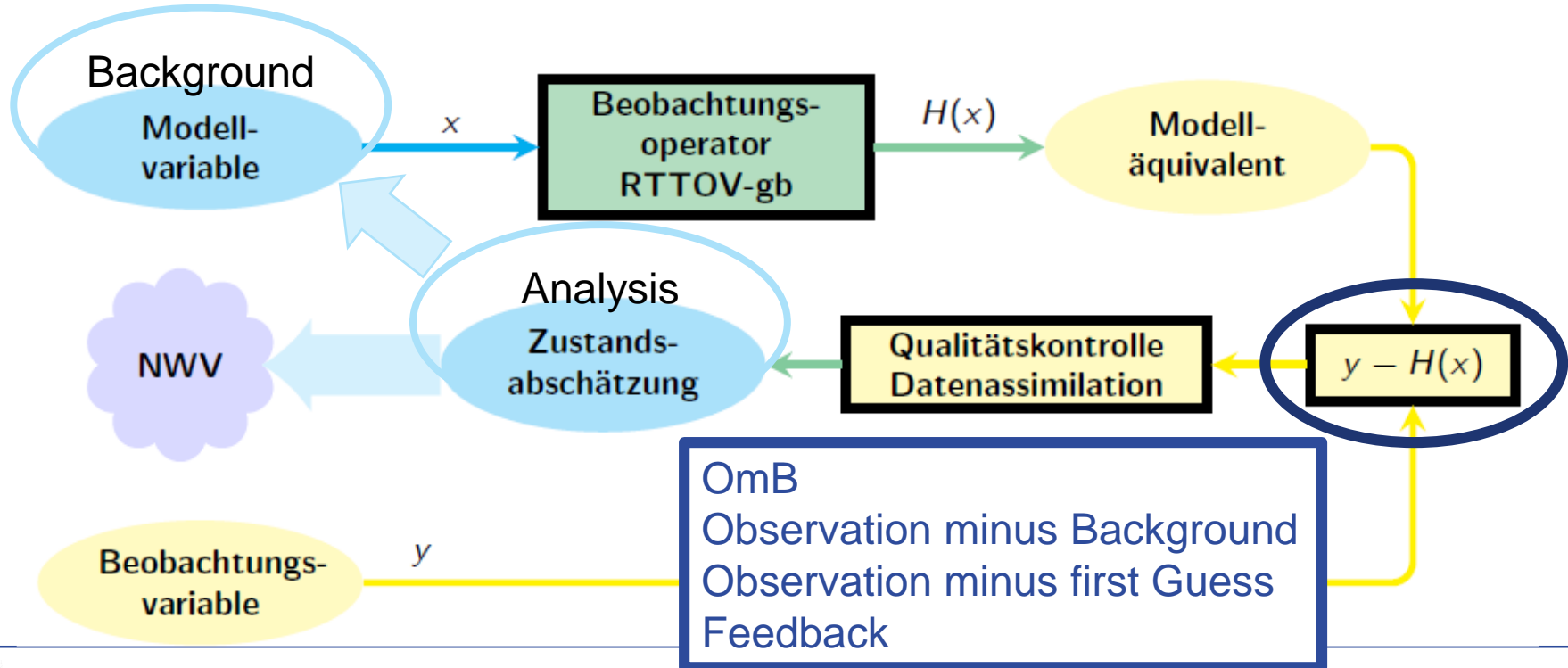
Sprectrum
Inconsistent

Data Assimilation



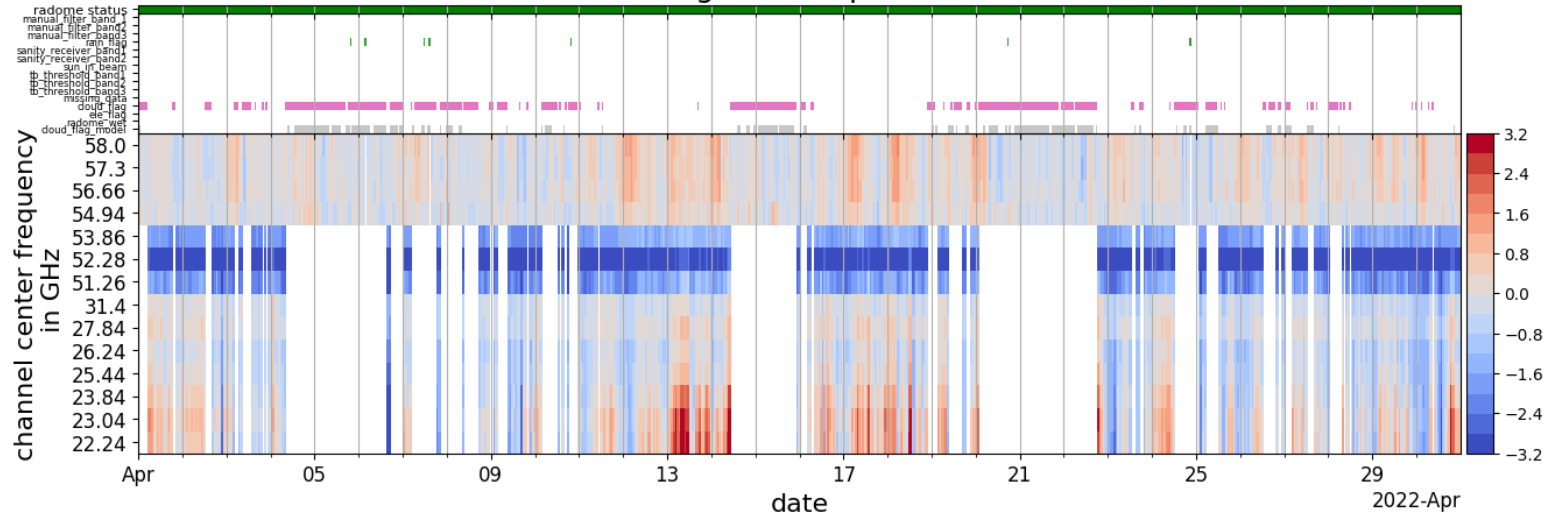
All steps performed in the observation space i.e. Brightness Temperatures (T_b) rather than retrieved thermodynamic profiles.

Assimilation of MWR Tb



MWR Observations minus Background (OmB)

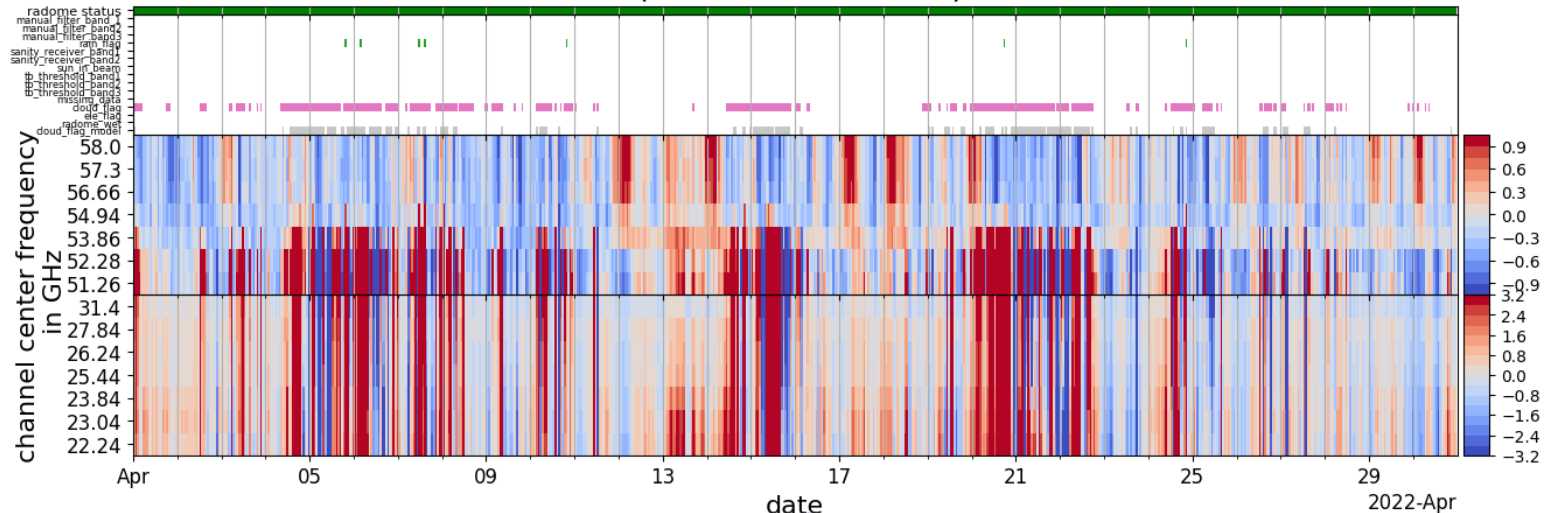
Obs. minus first guess HatproG5 LG - ICON-D2



Cloudy and rainy cases are masked

MWR OmB including cloudy data

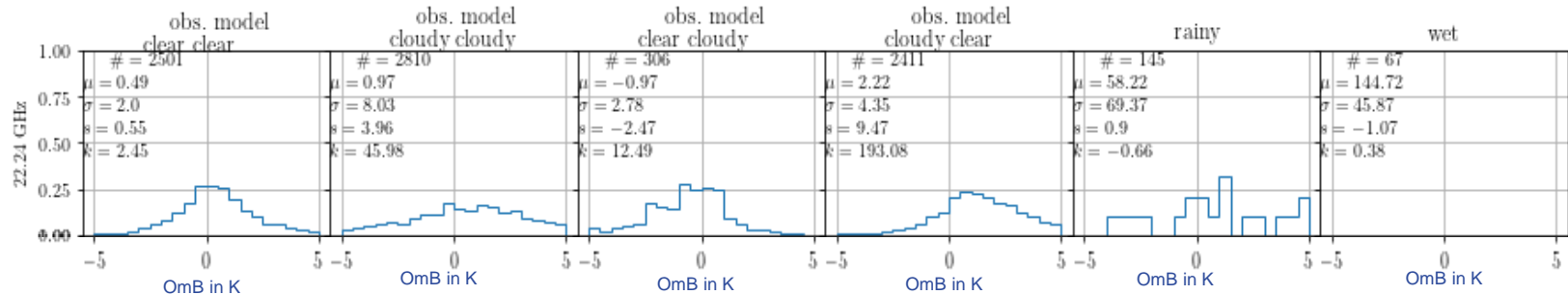
Obs. minus first guess HatproG5 LG - ICON-D2
(with static bias corr)



The displayed data include a bias correction to account for the systematic deviations

- Significant differences in presence of liquid water are visible
- Transient deviations (clear-sky) indicate the information content with respect to the model background

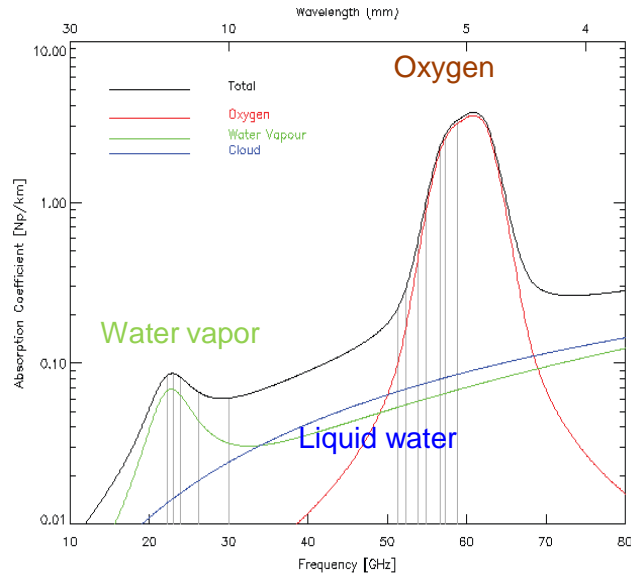
Impact of Cloud Liquid Water and Rain



Histogramme von Beobachtung (MWR @ Lindenberg) minus Background (ICON-D2) from Okt. '20 to Dez. '21 sortiert nach detektiertem Einfluss von Flüssigwasserwolken in Beobachtung bzw. Model. Nur TB_{MW} @ 22.2GHz.

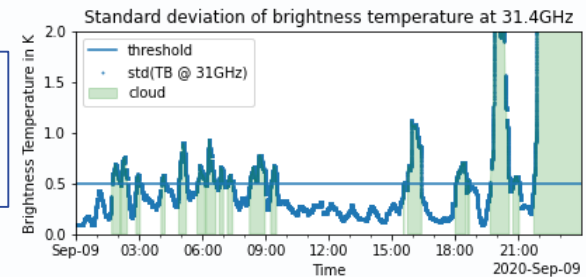
- In presence of clouds, the distributions are skew, asymmetrical und broad.
- In presence of rain or dew: very large mean deviations due to signals of non atmospheric origin

Impact of Cloud Liquid Water (and Rain)

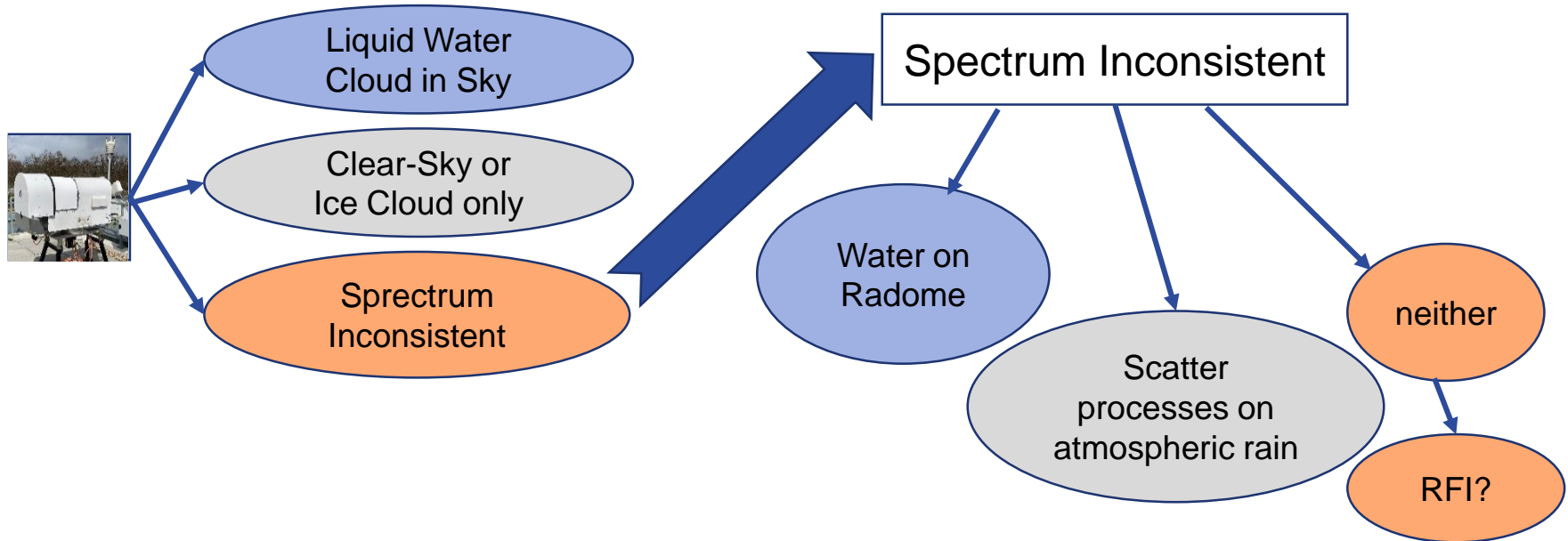


- K-Band and transparent part of V-Band are sensitive to cloud liquid water
- Small scale variability of liquid water causes a error of representativity in model comparisons
- Variability of T_b and Liquid water path are known indicators for detecting cloud liquid water.

Std of
 T_b @31
GHz

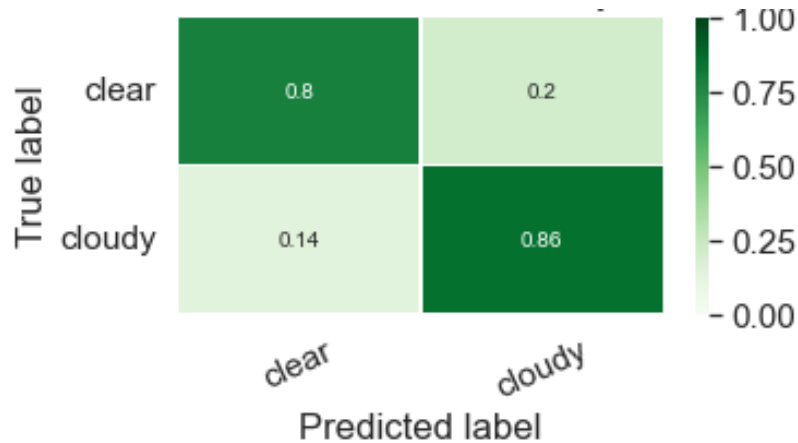


Cloudy/Clear-sky Classification



Detect Liquid Water Clouds

Performance of the empirical method



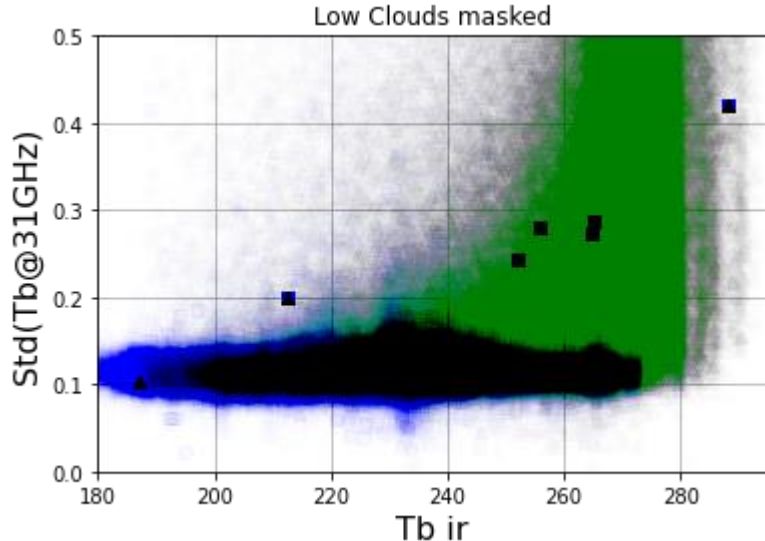
Rate of detection of liquid water clouds using the CloudNet target classification as a ground truth reference.

New Development

- Develop a machine learning based algorithm with
 - low latency,
 - geographic independence,
 - few requirements to additional instrumentation
 - applies to all elevation angles
- Aiming to obtain a standard algorithm which is accepted and used within ACTRIS and E-profile.
- Develop a method which assesses the spectrum consistency and can also be used for quality checks.

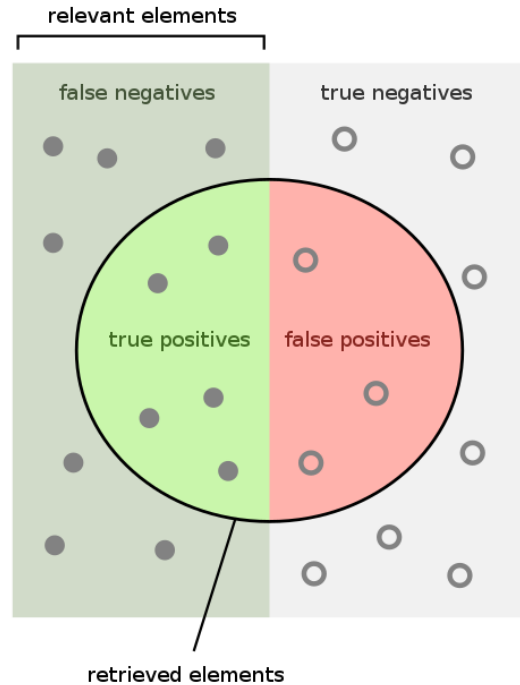
First look into data and filtering

Observed data with cloud info



- Using CloudNet target classification as a ground truth for evaluating classification algorithms.
- **clear-sky**, **cloudy** and **overlapping**
- Removing cases with **rain** (**rainsensor**)
- Removing cases with **rain** (**distrometer**)
- Add undetected **low clouds** to CloudNet classification
- Final dataset which I'll be using in the following

Precision and Recall



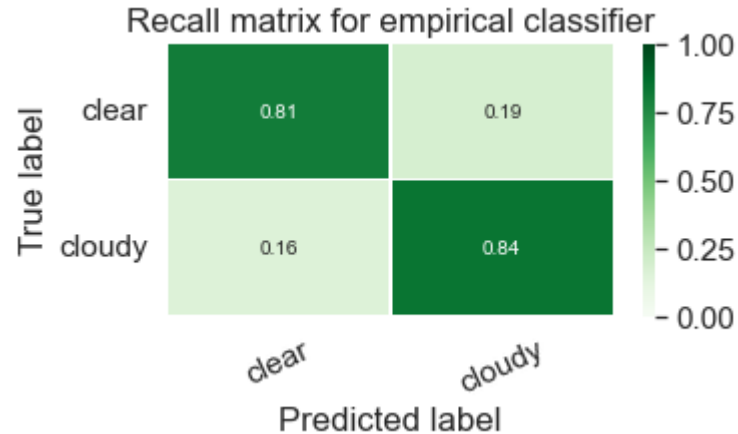
How many retrieved items are relevant?

$$\text{Precision} = \frac{\text{true positives}}{\text{true positives} + \text{false positives}}$$

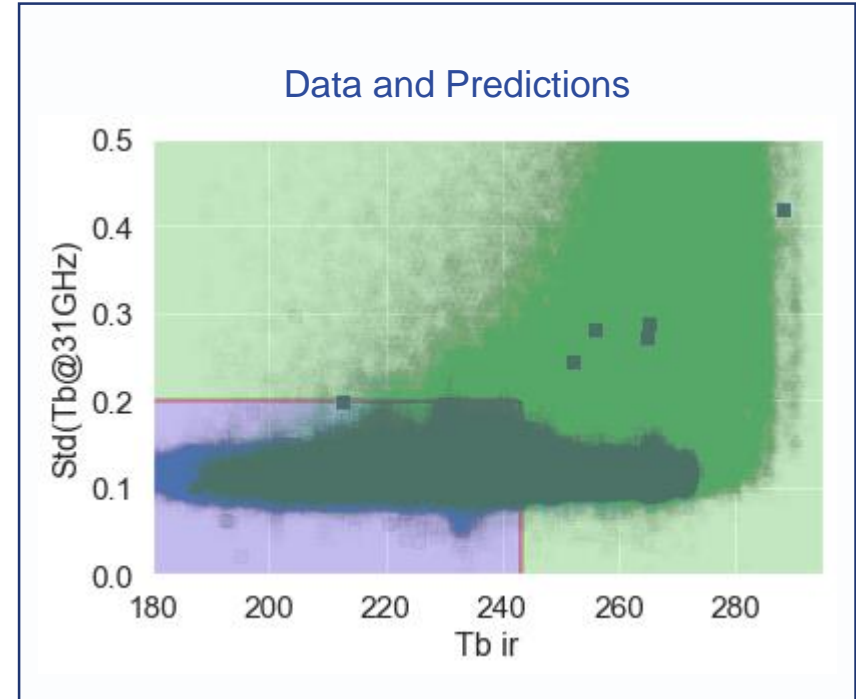
How many relevant items are retrieved?

$$\text{Recall} = \frac{\text{true positives}}{\text{true positives} + \text{false negatives}}$$

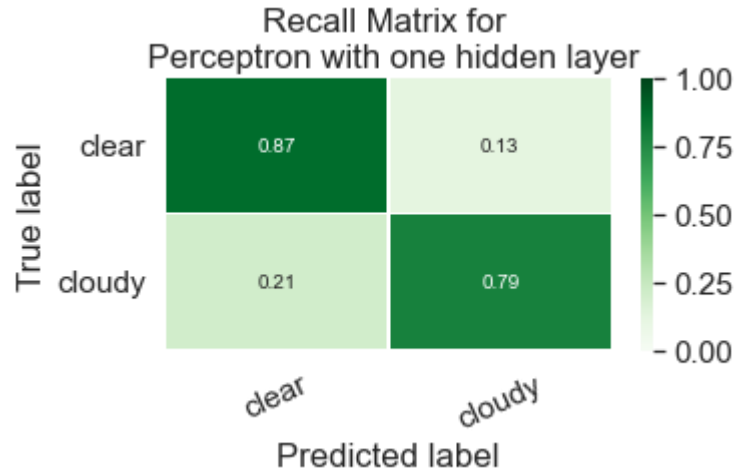
Empirical Method



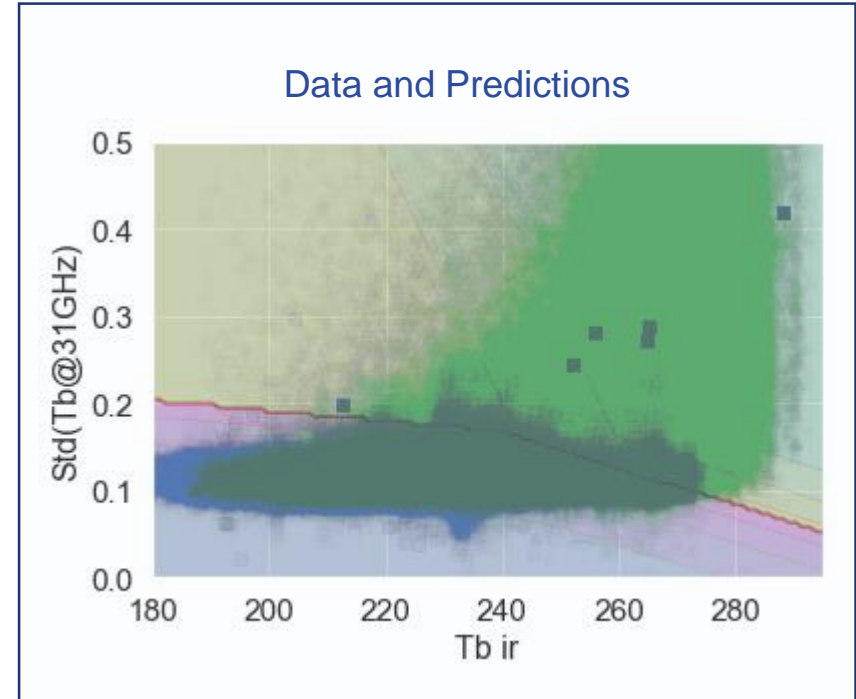
- Performance of empirical method is benchmark for new developments
- Overlapping structure of dataset complicates separation of clear and cloudy cases.
- The presence of liquid clouds at very low TbIR indicates issues with CloudNet classification as a „True“ reference



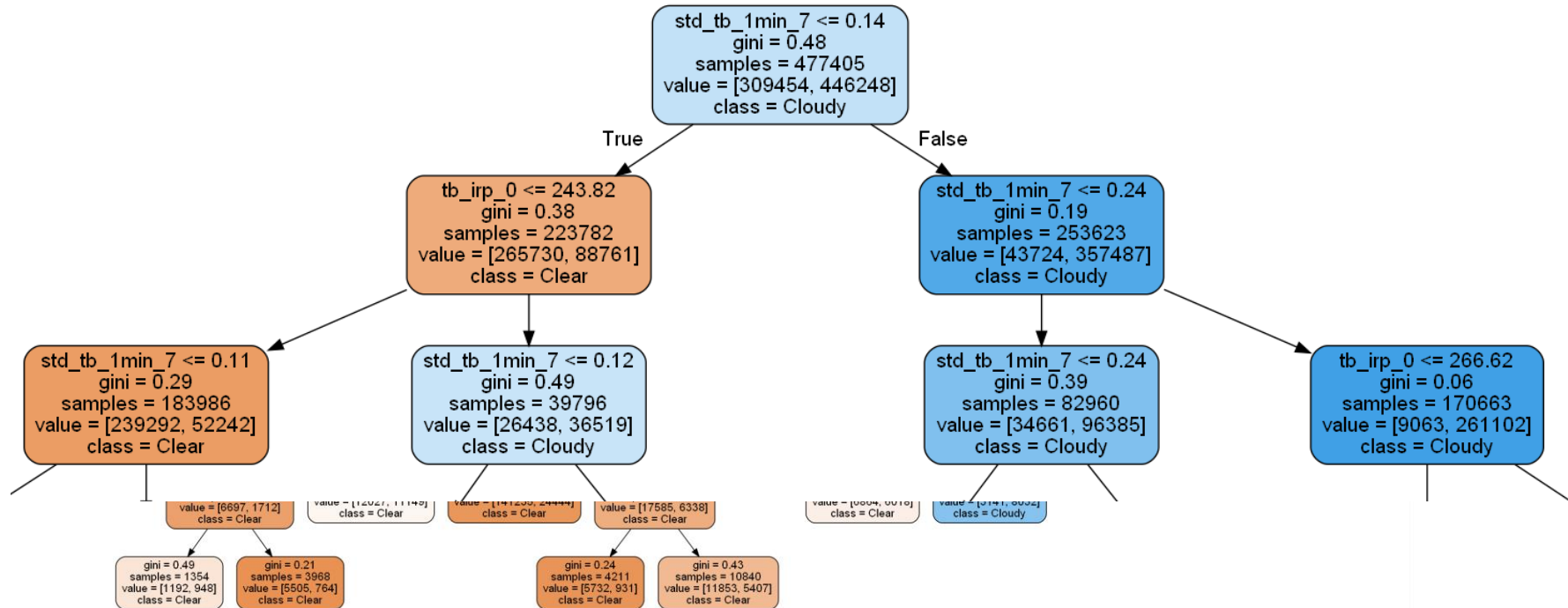
Neural Network with 1 hidden layer (Perceptron)



- Performance is typical for ML based algorithms.
- ML based approaches result in small improvements with respect to the empirical method.
- Including additional dimensions for predicting has a small impact on precision and recall

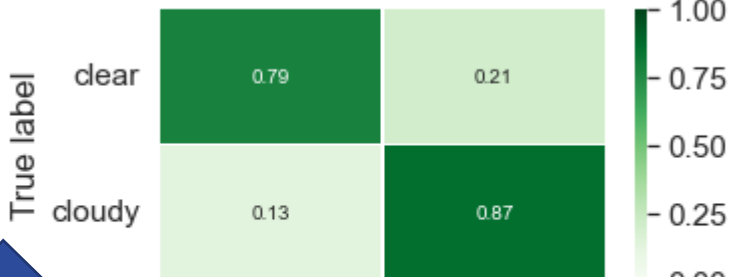


Decision tree -> random forest (tree ensemble)

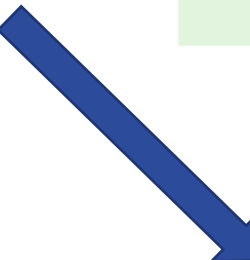
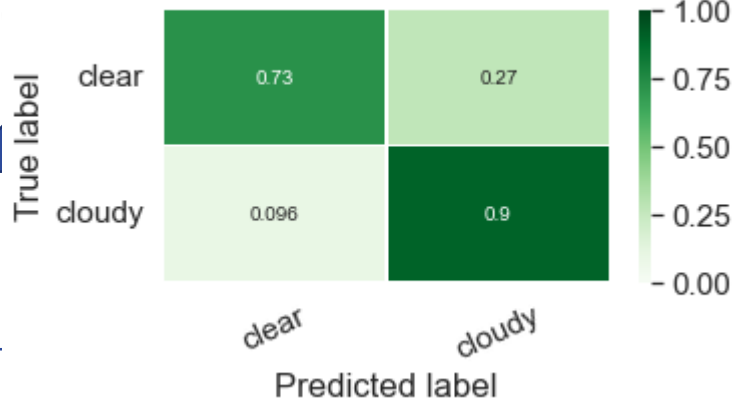


Random Forest

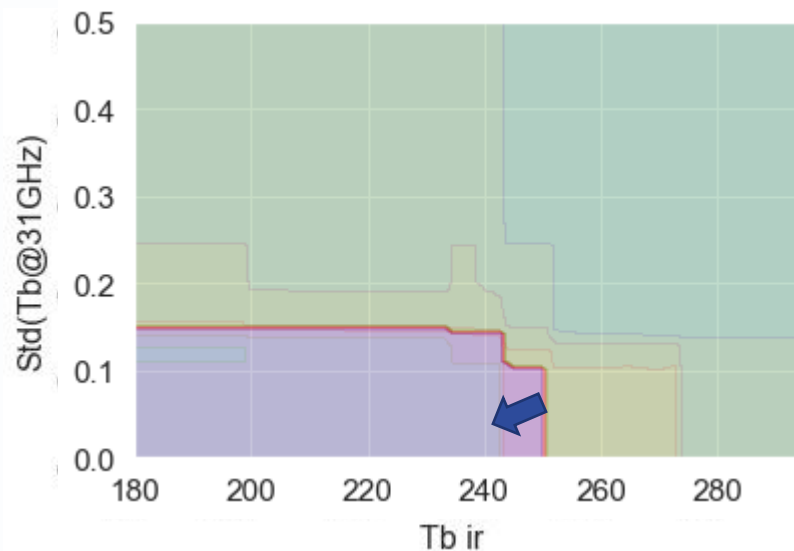
Recall matrix for random forest classifier



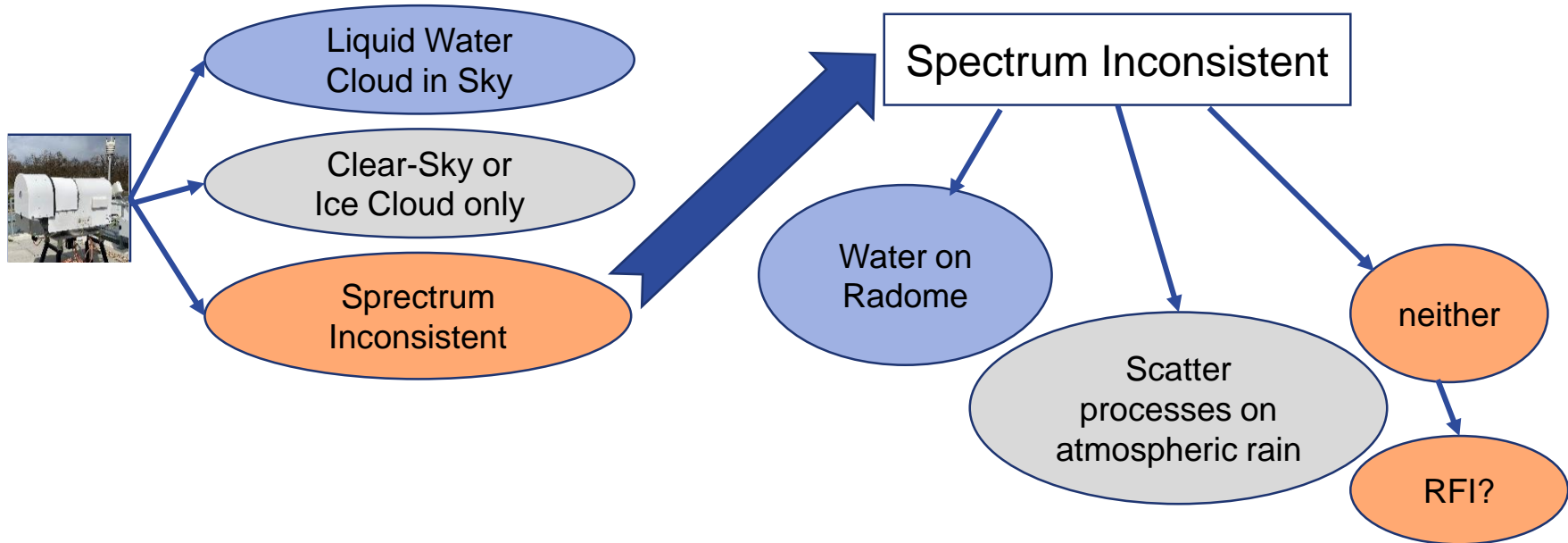
Recall Matrix for Random Forest Classifier



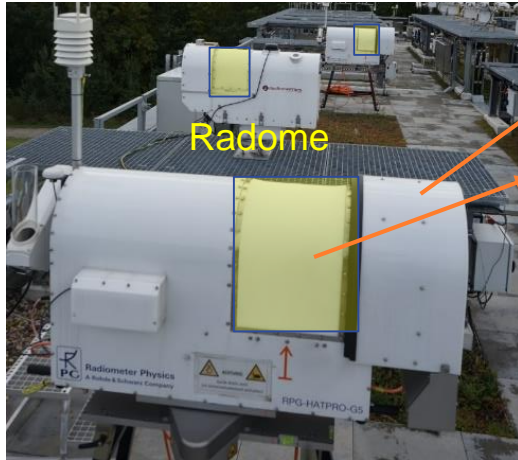
Data and Predictions



Spectral consistency

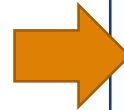


Liquid water on the radome



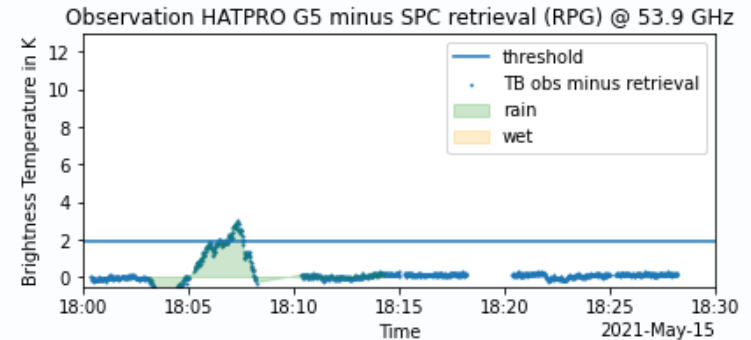
The radome is kept dry with:

- heater, blower and rain sensor
- Hygroscopic coating



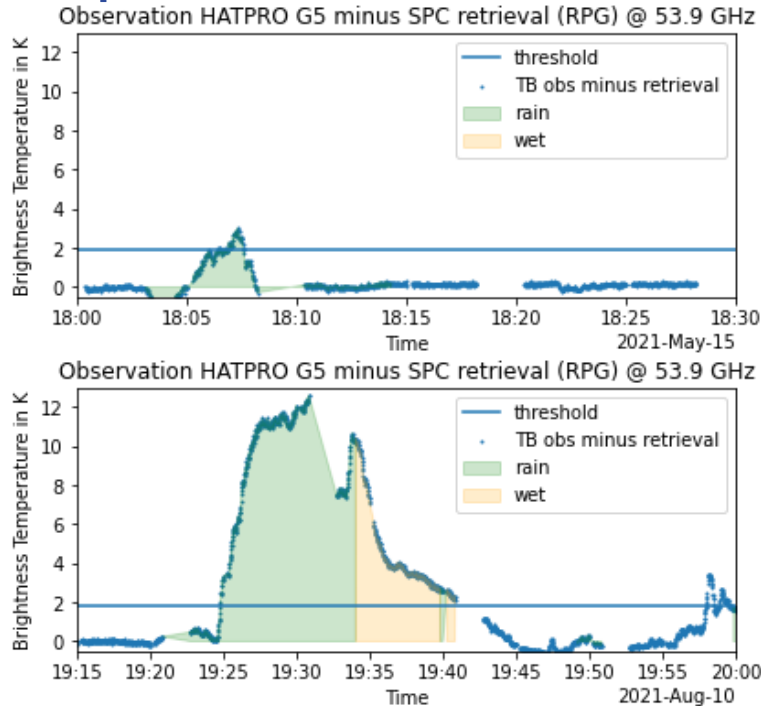
Automatic identification of water on the radome (e.g. after rain events):

Evaluation of spectral consistency of Tb data: Tb observations vs. Tb spectral retrieval from neural network retrieval algorithm (LV2 product)

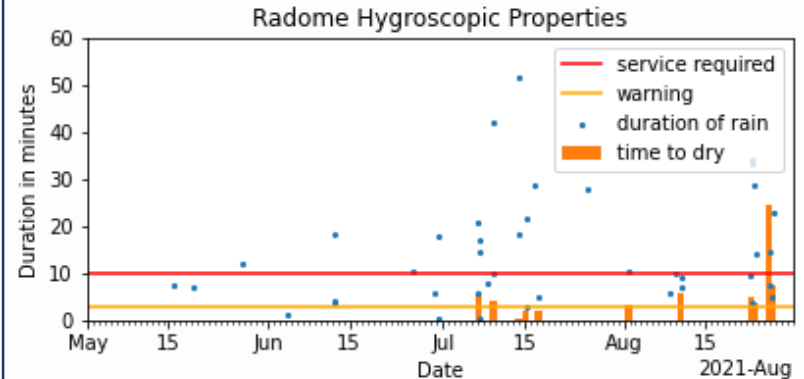


FESSTVaL campaign summer 2021
@Lindenberg

Liquid water on the radome

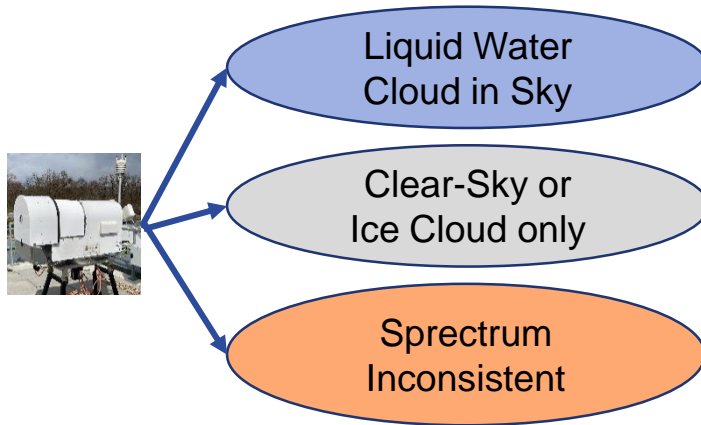


Continuous evaluation of spectral consistency of Tb data **during and after rain** provides an indication of radome degrading:



➤ Radom quality flag: Warnung und Wartung

Outlook



- Cloudy/clear-sky classification and spectral consistency checks based on
 - Reanalysis and radiative transfer modelling,
 - Observed data
- which
 - has few requirements to additional instrumentation
 - applies to all elevation angles
 - is simple and fast

Thank you!

Kontakt:

Moritz Löffler

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