

Recent improvements of CML rainfall estimation and CML-Radar combination in Germany

Click



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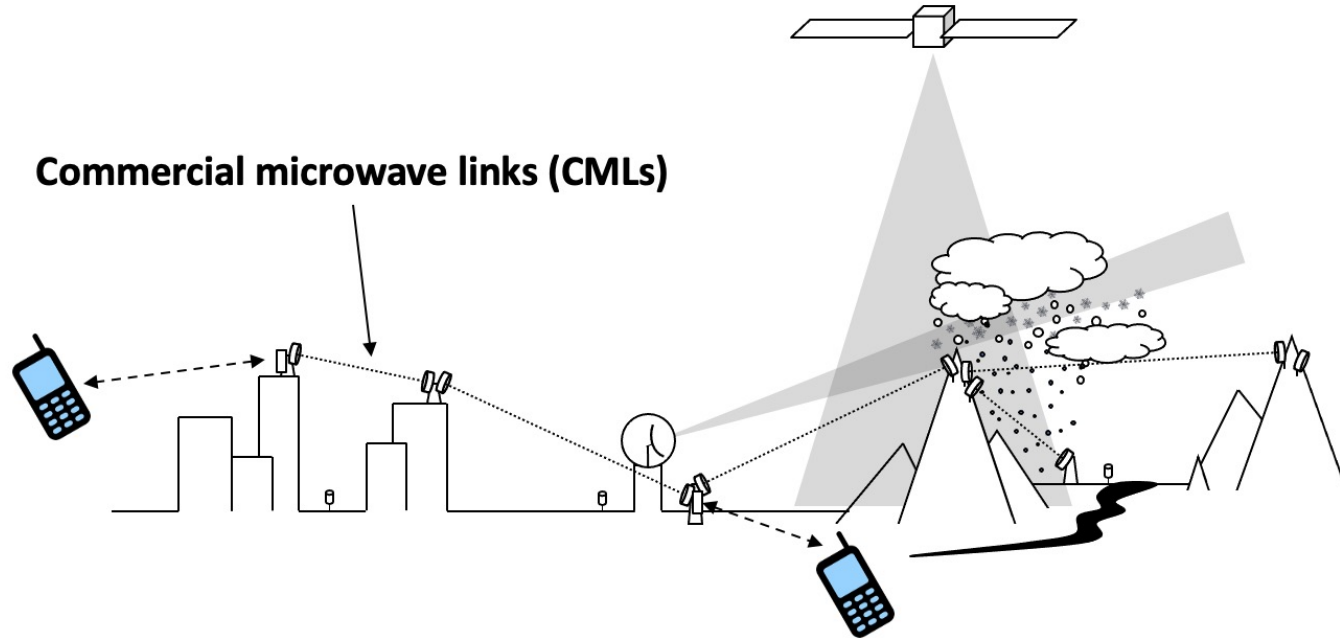
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2 Institute for Geography, University of Augsburg, Augsburg, Germany

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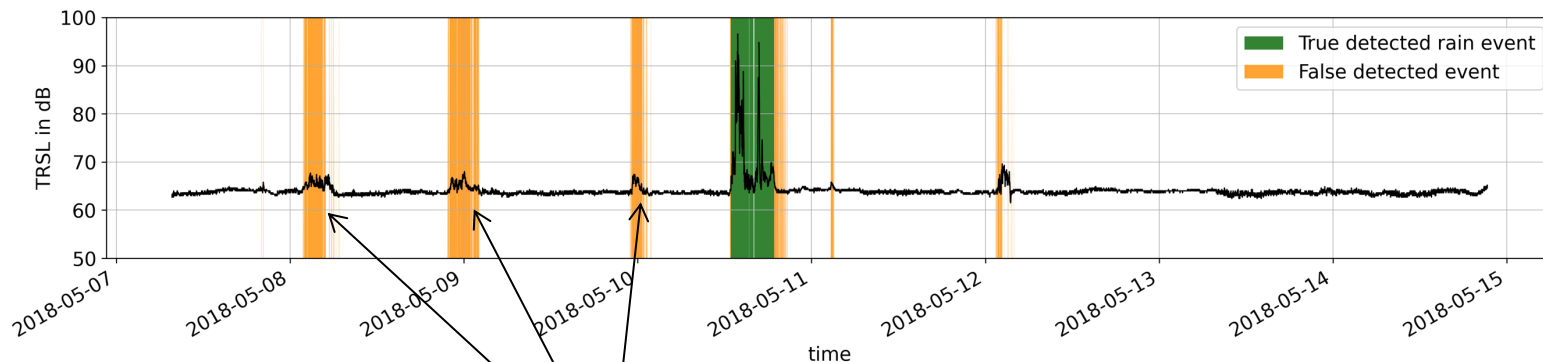
CMLs provide large parts of the backbone of the cellular network and can provide rainfall information in addition to existing observations also in regions where these are scarce



1. Detecting erratic signal fluctuations

CMLs have not been designed to be rainfall sensors - Their raw data can show erratic signal fluctuations

Signal fluctuations not caused by rainfall induced attenuation can lead to false detected rain events.

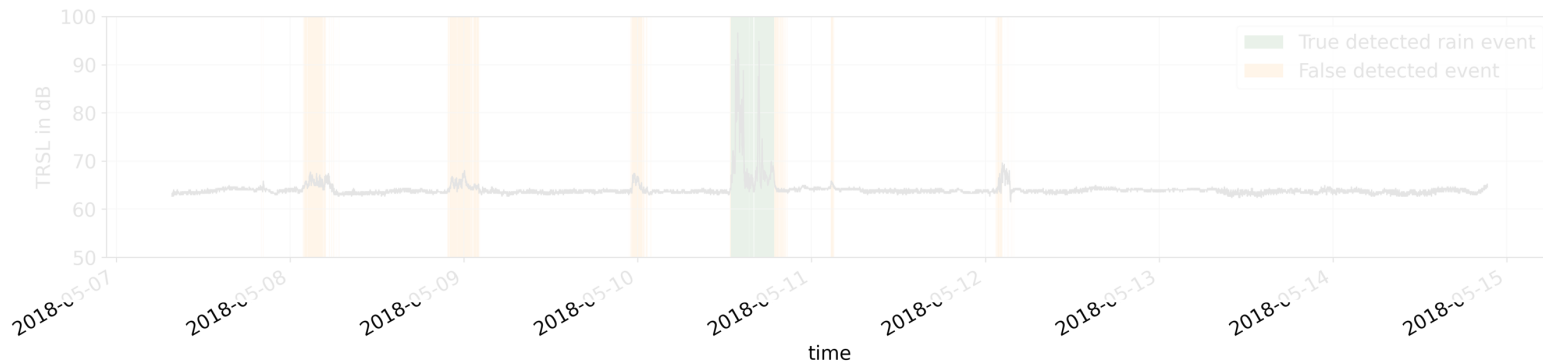


Up to now, some CMLs have, therefore, been excluded from the rainfall estimation.

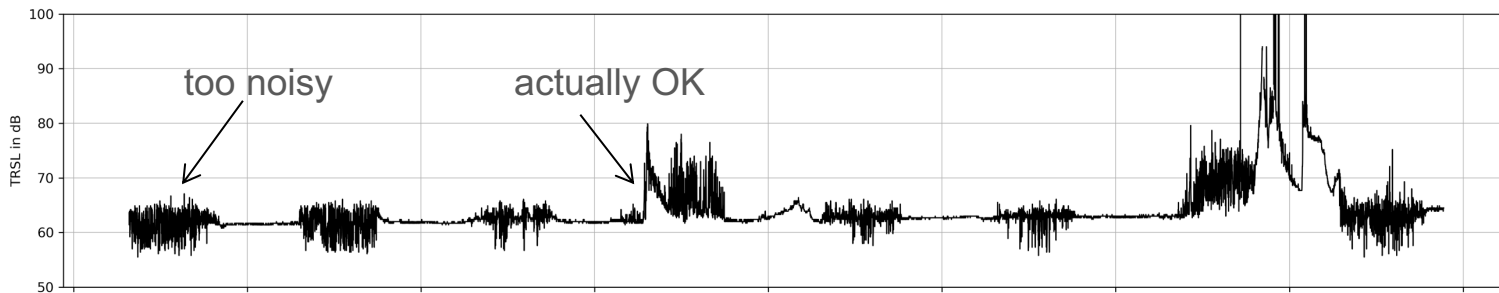


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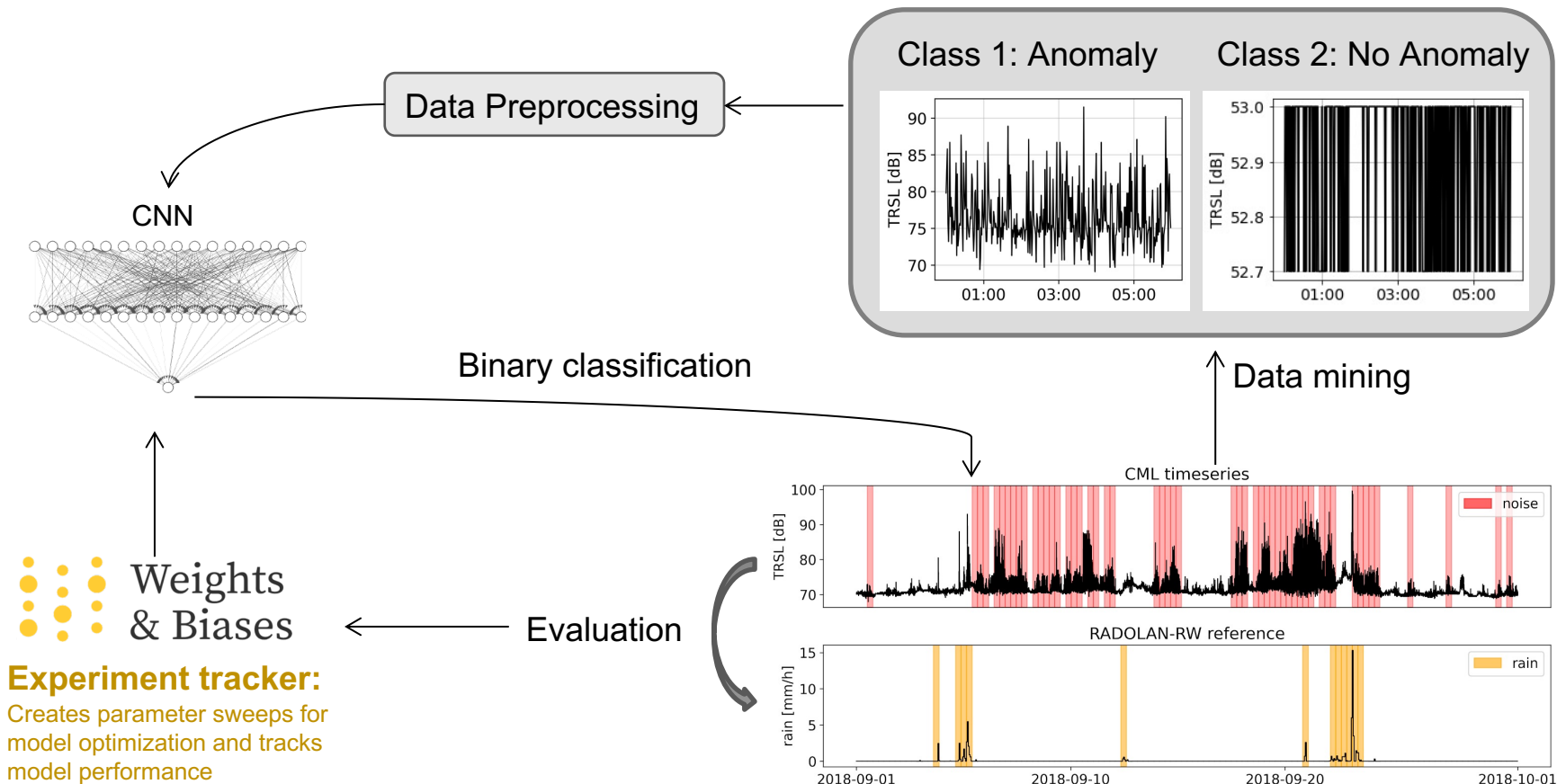
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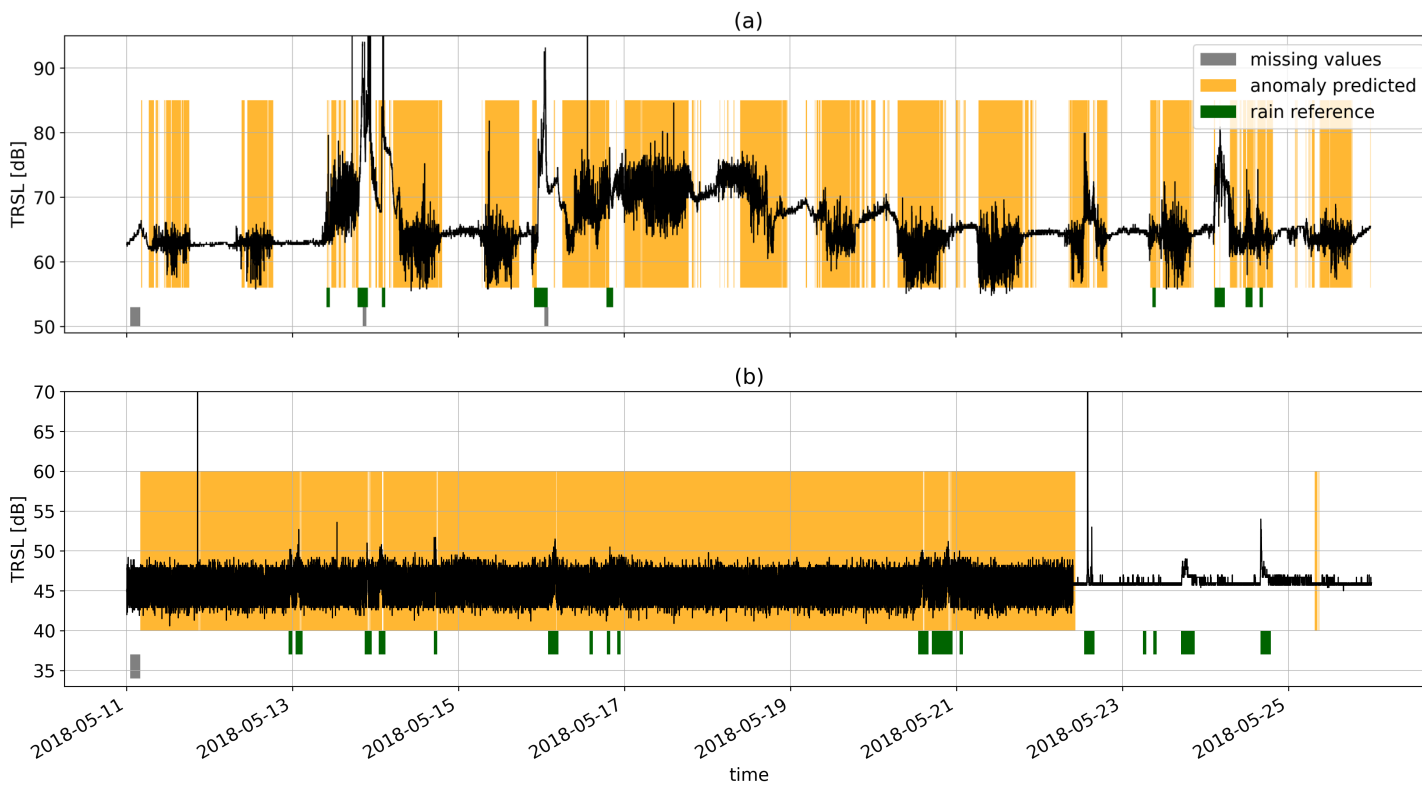
Up to now, some CMLs have, therefore, been excluded from the rainfall estimation.



Solution: Anomaly detection through neural networks



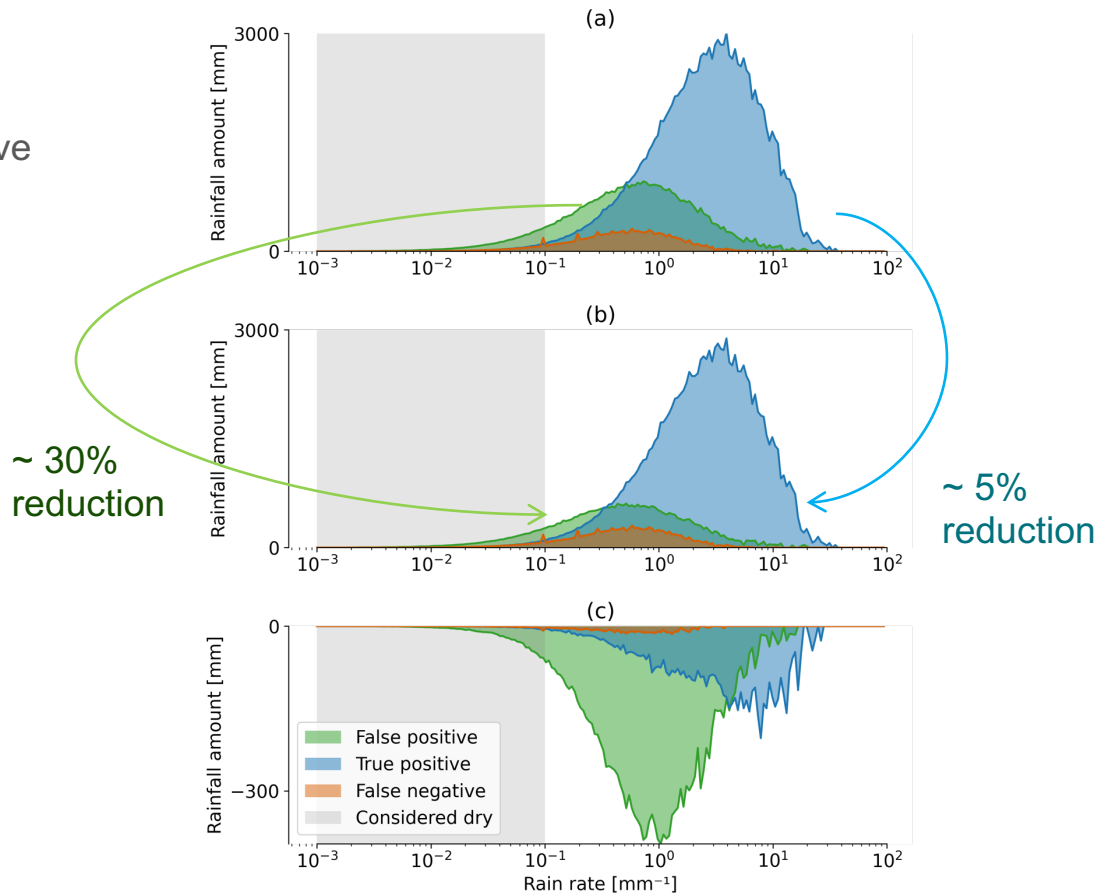
Possibility of using previously excluded CMLs...



Positive effect on false-positives

- Rainfall amount of different rain rates contributing to false positive, true positive and false negative rainfall according to the radar reference (see slide 18):

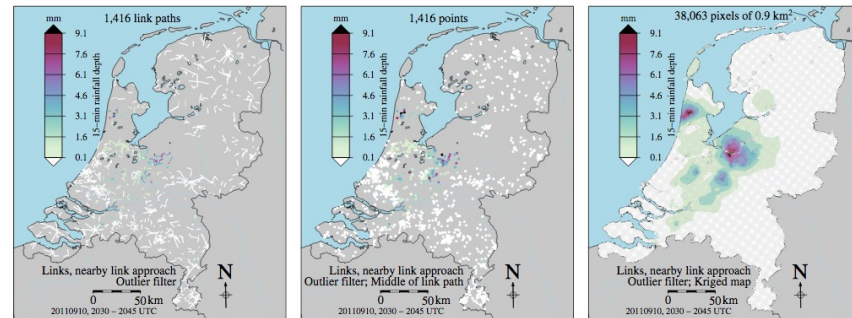
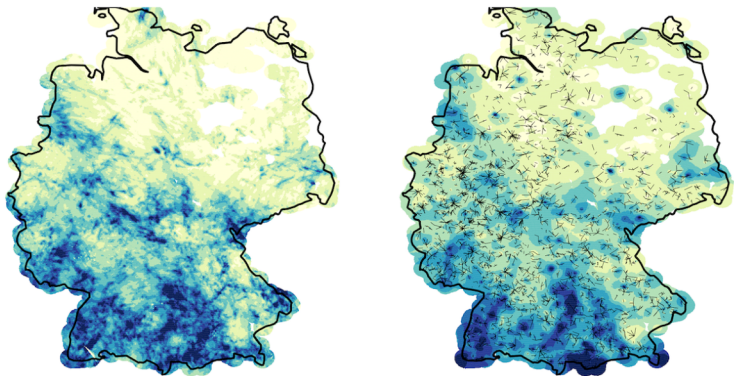
- Rainfall estimated in September 2018
- Same data without detected anomalies
- Difference between (b) and (a)



2. Large scale method intercomparison

We compare the two different processing approaches that have been used for country-wide CML rainfall estimation

- Time-series based processing of individual CMLs
- Validated for 4000 CMLs in Germany
- Methods available in [pycomlink](https://doi.org/10.5194/hess-24-2931-2020)
- Processing based on correlation in data of neighboring CMLs
- Validated for 1500 CMLs in the Netherlands
- Methods available in [RAINLINK](https://doi.org/10.5194/amt-9-2425-2016)

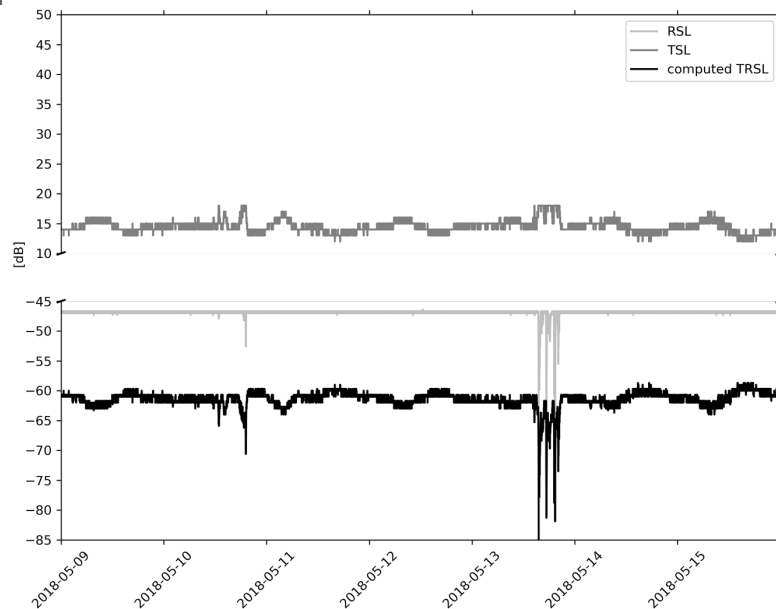


Implementation of RAINLINK algorithm in Python

- Steps of implementation (based on Overeem et al. 2016):
 - importing given example data from RAINLINK package
 - processing as pandas data frame showed 100% consistency
 - changing data structure to xarray -> 100% consistency and benefits:
 - multiple channels can be computed independently or together
 - used data structure is more flexible and performant
 - easy parallelization (e.g. dask)
 - computation of German wide CML data is now easily feasible with the nearby link approach

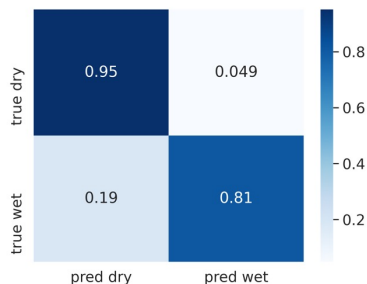
How does the computation work?

- used data consists of 1min instantaneously sampled resolution with varying TSL instead of 15min min/max
- Following steps:
 1. $\text{computed TRSL} = (\text{TSL} - \text{RSL}) \cdot -1$ (see plot)
 2. aggregation to 15min with $\min(\text{comp_TRSL})$
 3. 24h-rolling max of aggregated comp_TRSL values
 4. $\text{deltaP} = \text{comp_TRSL} - \max(\text{comp_att})$
 $\text{deltaPL} = \text{deltaP} / \text{length of link}$
 5. if median of all deltaP or deltaPL in vicinity (nearby links) < threshold, an interval is classified as wet

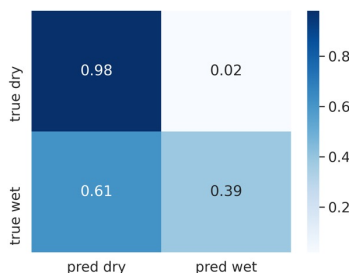


Comparison of wet-dry classification for September 2018 with RADOLAN-RW as reference

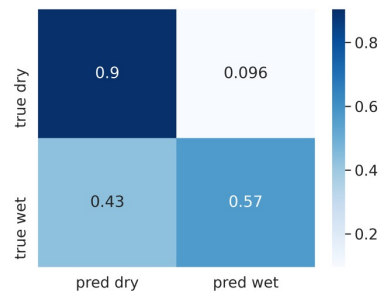
CNN method (Polz et al. 2020)
shows good results:



RAINLINK with standard
thresholds



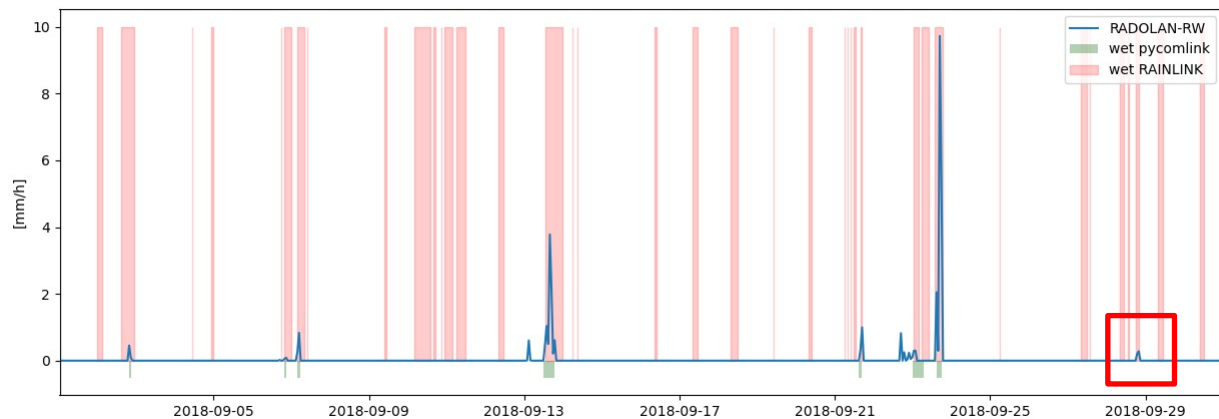
RAINLINK with thresh. $\Delta PL = -0.25$
and $\Delta P = -1.4$



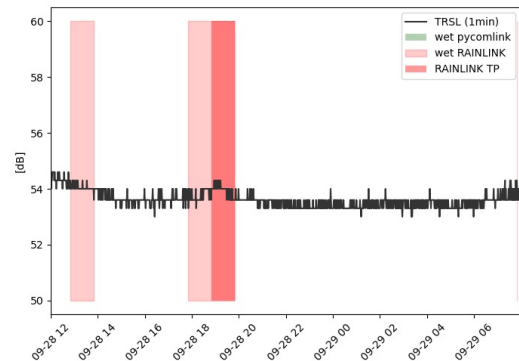
Using standard thresholds, RL shows a strong underestimation of wet periods. This is probably due to longer average link paths in Germany (7.6km).

Using “ $\Delta PL > -0.3$ ” increases the TP rate, but (as always) at the cost of the FP rate

Both methods show advantages, hence, a combined application is envisaged...



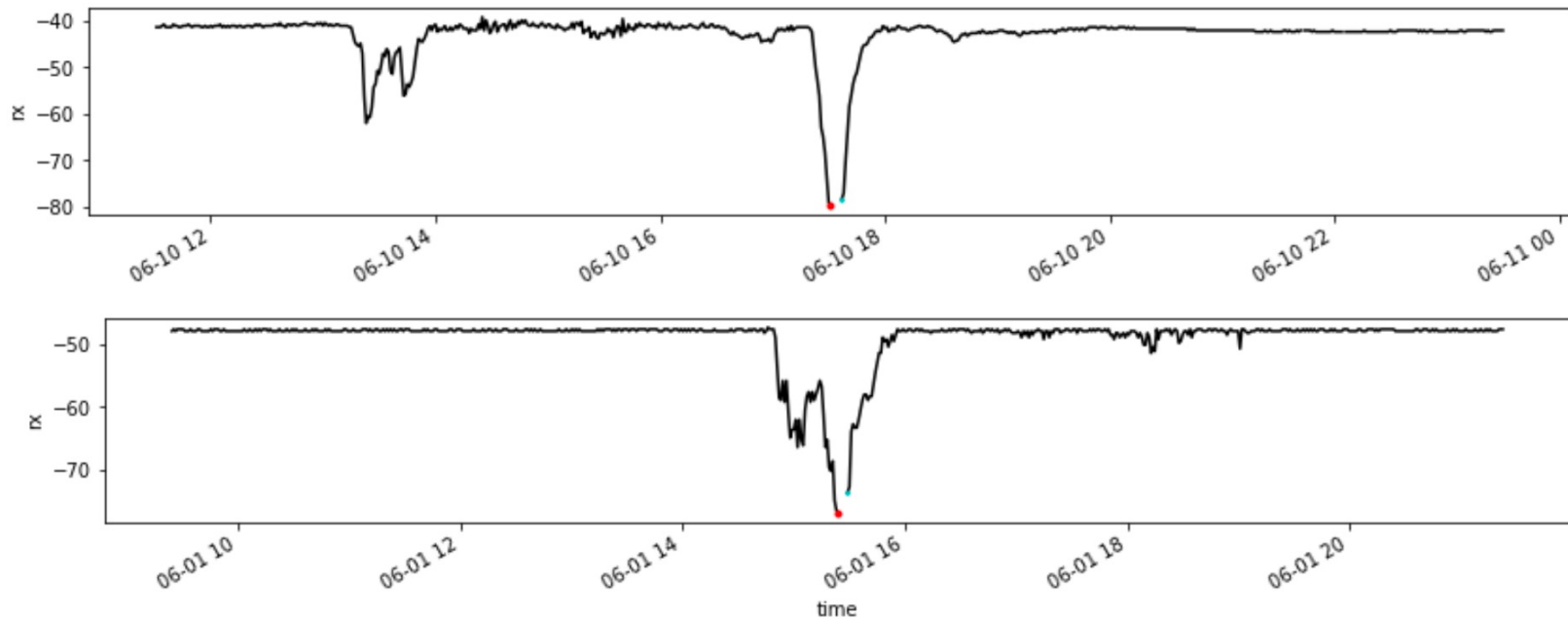
The implementation of RAINLINK in Python might help to see rain events better. There is still a lot of adjusting necessary.



3. The effect and mitigation of data gaps during heavy rainfall

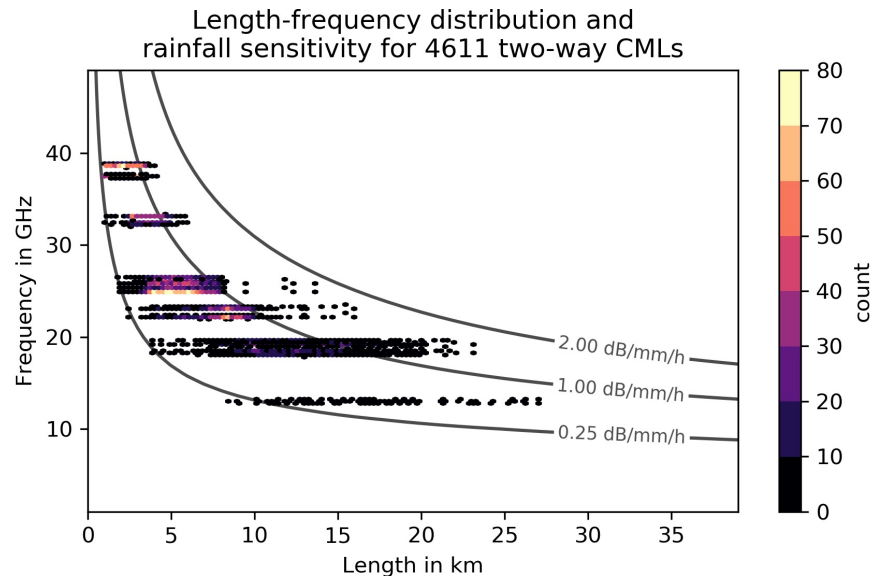
CMLs can experience complete loss of signal (blackout) when attenuation is too large for the receiver to operate

- Below a certain RSL (here at -80 dBm) no attenuation data can be recorded due to non-functioning communication along the CML

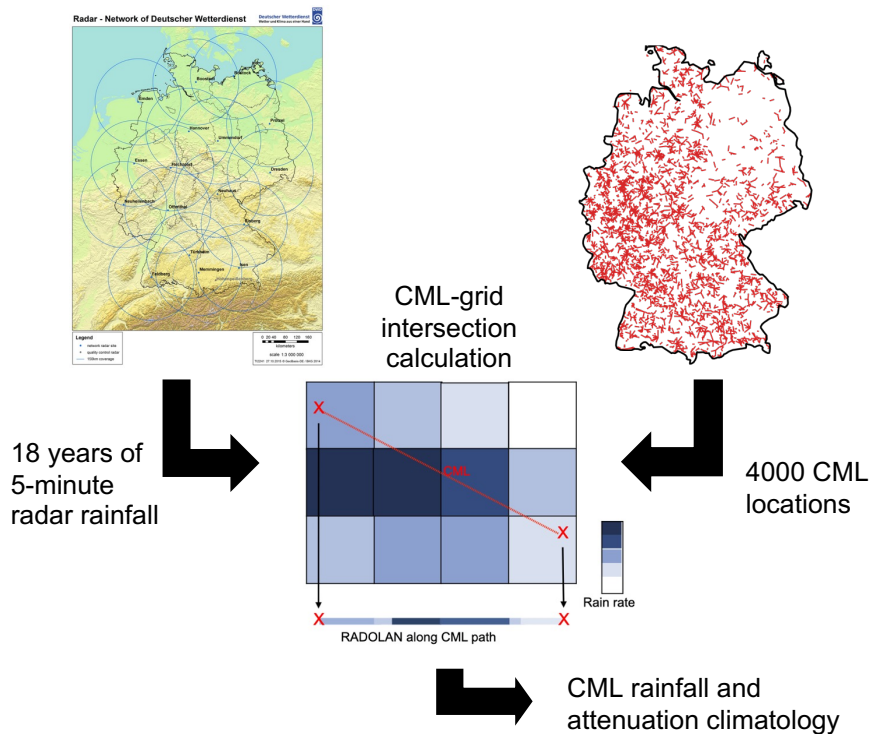


CML networks are planed so that blackouts statistically only occur approximately 0.001% of the time, i.e. 5 minutes/year

- Length and frequency of CMLs are chosen so that the sensitivity due to rainfall (iso lines in the plot) is in the range of 1.0 dB/mm/h
- The likeliness of high values of path-averaged rainfall increases with decreasing link length. Hence, spatial rainfall statistics are required to get a clearer picture
- (the iso lines in the plot assume homogeneous rainfall distribution along the path)



We study the likeliness of blackouts using synthetic 5-minute CML observations generated from 18 years of RADKLIM-YW

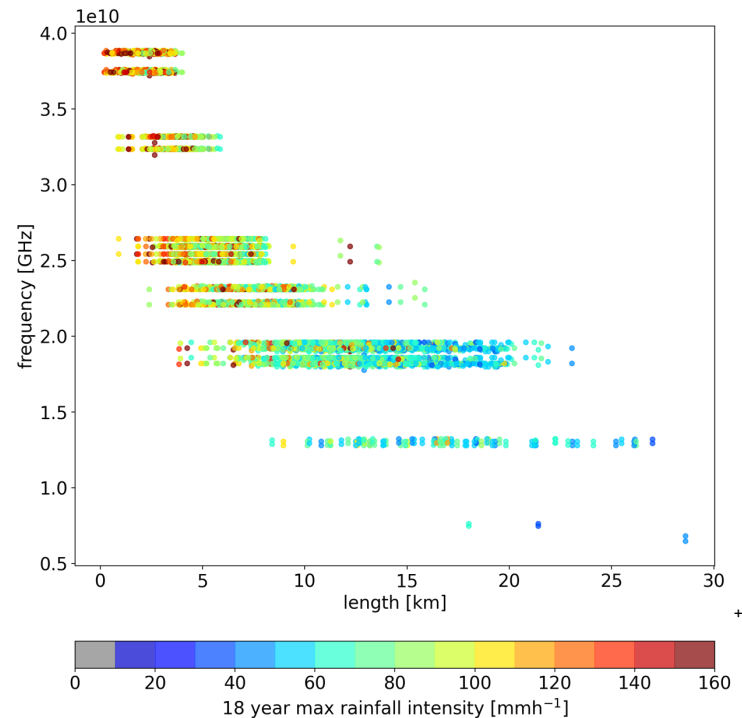
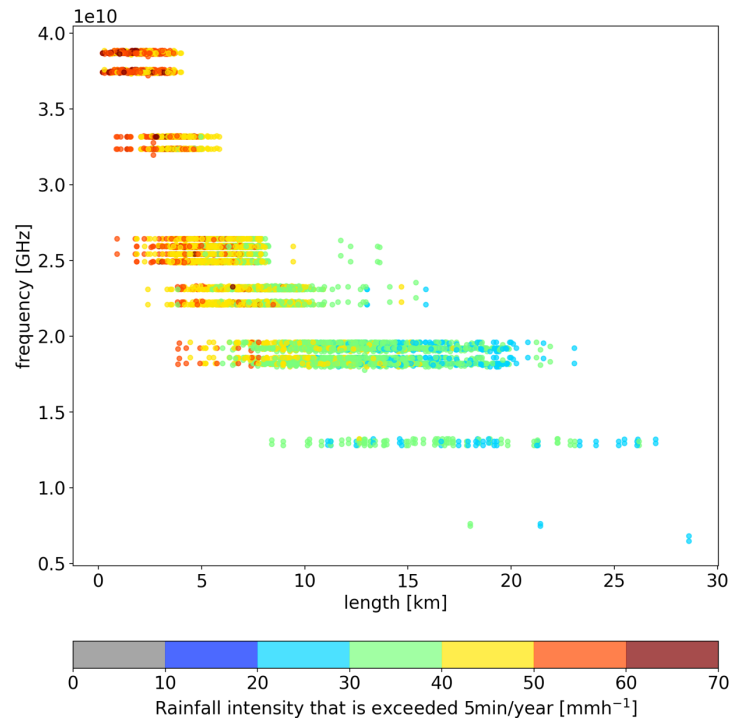


- Using the gauge adjusted radar climatology RADKLIM-YW with a 1km spatial and 5 minute temporal resolution, we can estimate the path integrated attenuation along the CML.
- Using 18 years of this data we can create a climatology of path averaged rainfall intensities that would lead to a blackout.

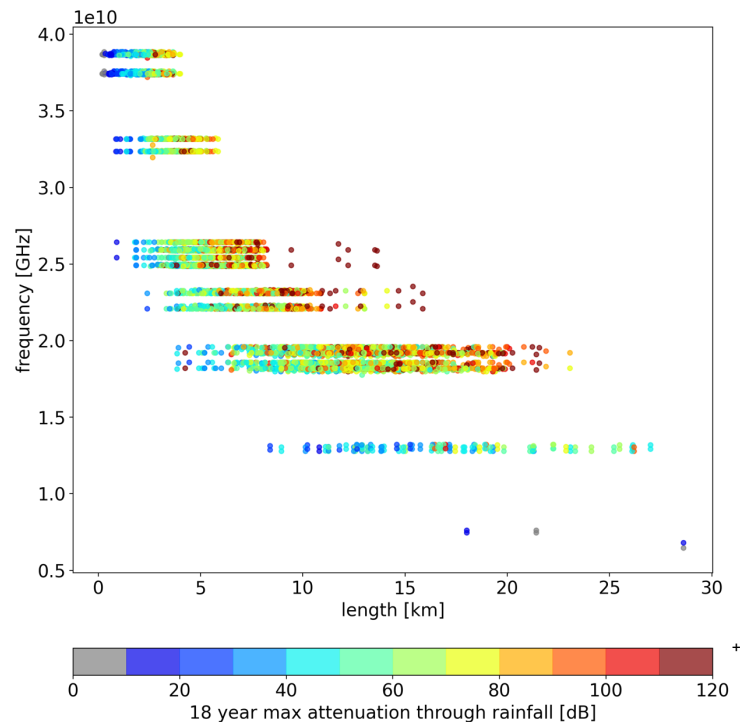
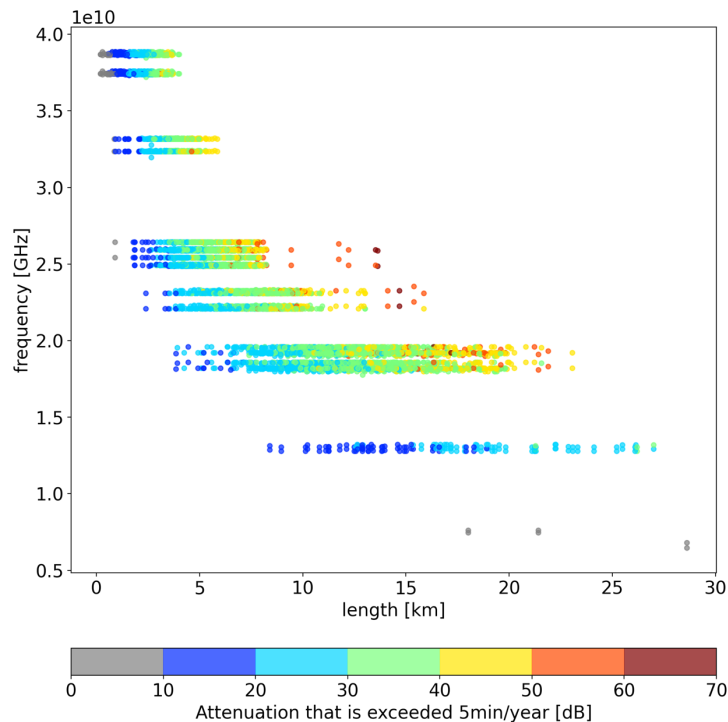
RADKLIM data: https://opendata.dwd.de/climate_environment/CDC/help/landing_pages/doi_landingpage_RADKLIM_RW_V2017.002-de.html

RADKLIM and RADOLAN NetCDF converter: https://github.com/cchwala/radolan_to_netcdf

As expected path-averaged rainfall rate maxima decrease with increasing CML length



The path-integrated attenuation maxima increase with increasing length despite the path-averaging of rainfall maxima

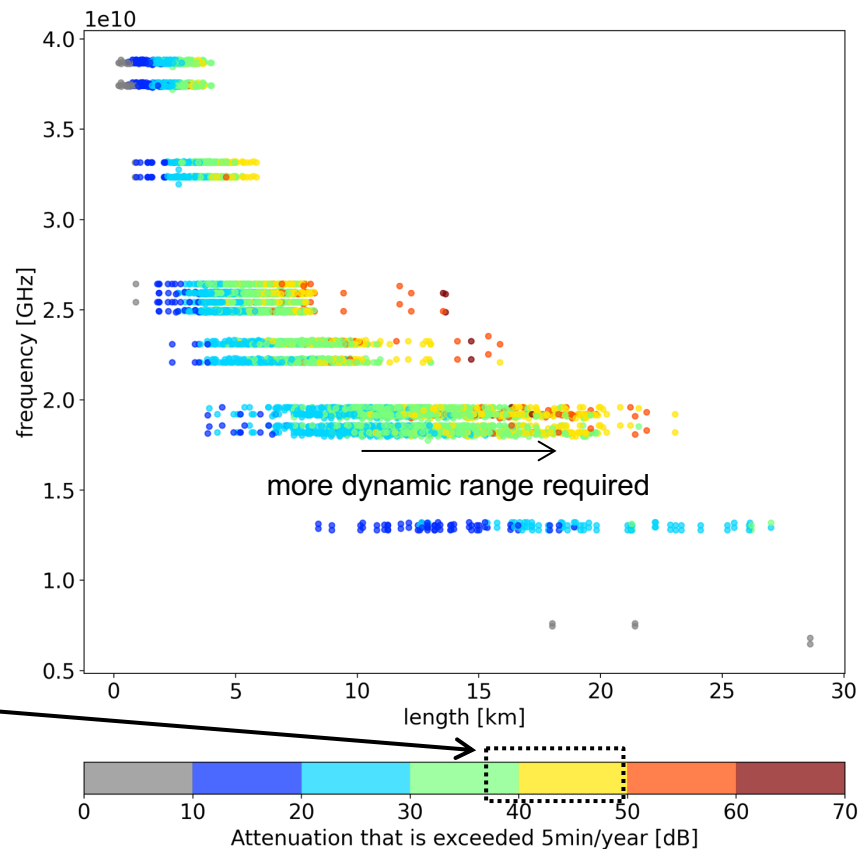


Blackouts depend on the dynamic range of CMLs

- Our long term statistics show that, according to the k-R power law as recommended by the ITU, 169 from 7808 CMLs exceed 50 dB and 1290 exceed 40 dB of attenuation for more than 5 minutes per year.

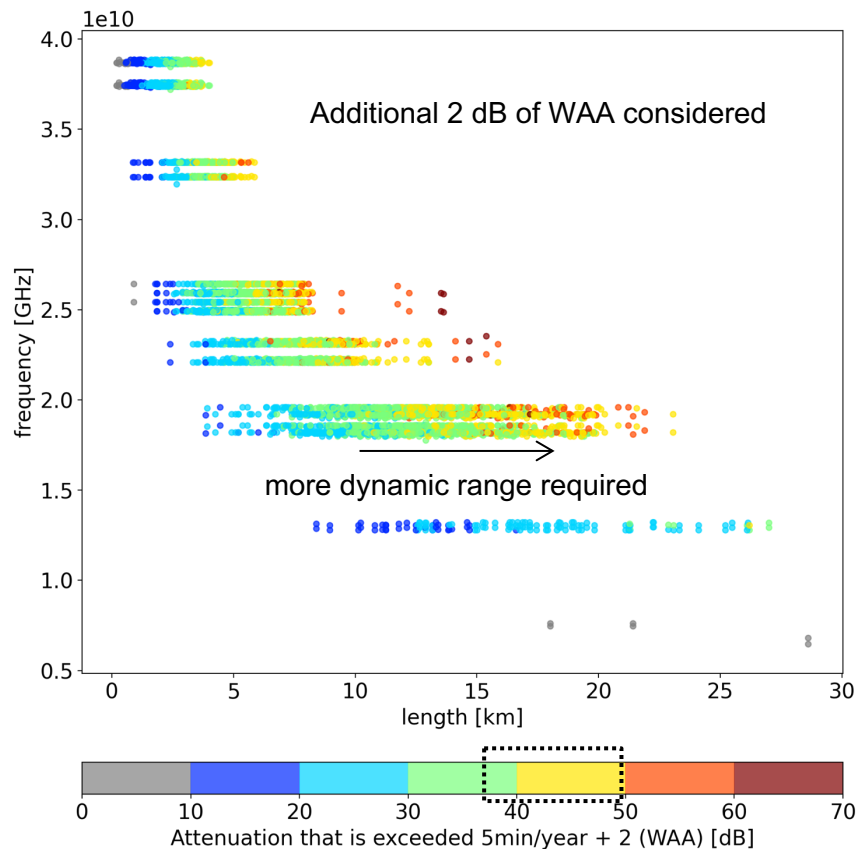
expected dynamic range of CMLs

- depending on
 - ATPC range
 - clear-sky RSL



Not only attenuation through rainfall should be considered

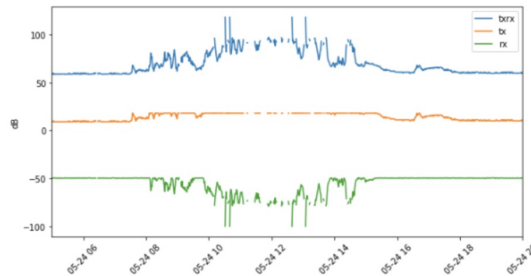
- However, additional attenuation can be created through wet antenna attenuation (WAA) and 1 minute rainfall will create higher extreme intensities.
- Therefore, more than 3% of all CMLs should experience a blackout at >50 dB of attenuation during, at least, the 5 minutes of highest rainfall intensity per year.



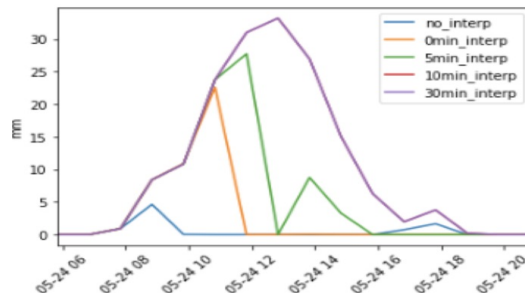
Mitigation of blackout gaps using simple interpolation

- Data gaps can be interpolated, e.g. using linear interpolation
- The question is: What is the maximum allowed length of a data gap
- Interpolating longer gaps, increases the estimated rainfall amount
- But, during the gaps, CMLs do underestimated rainfall because the attenuation would be higher than the observed one
- Better to set hours with “long” (how long?) gaps to Nan

Raw data with gaps



Resulting 1-hour rain fall sum for interpolation up to different gap length



temporal interpolation of gaps

4. Real-time applications

4a. CML-radar combination

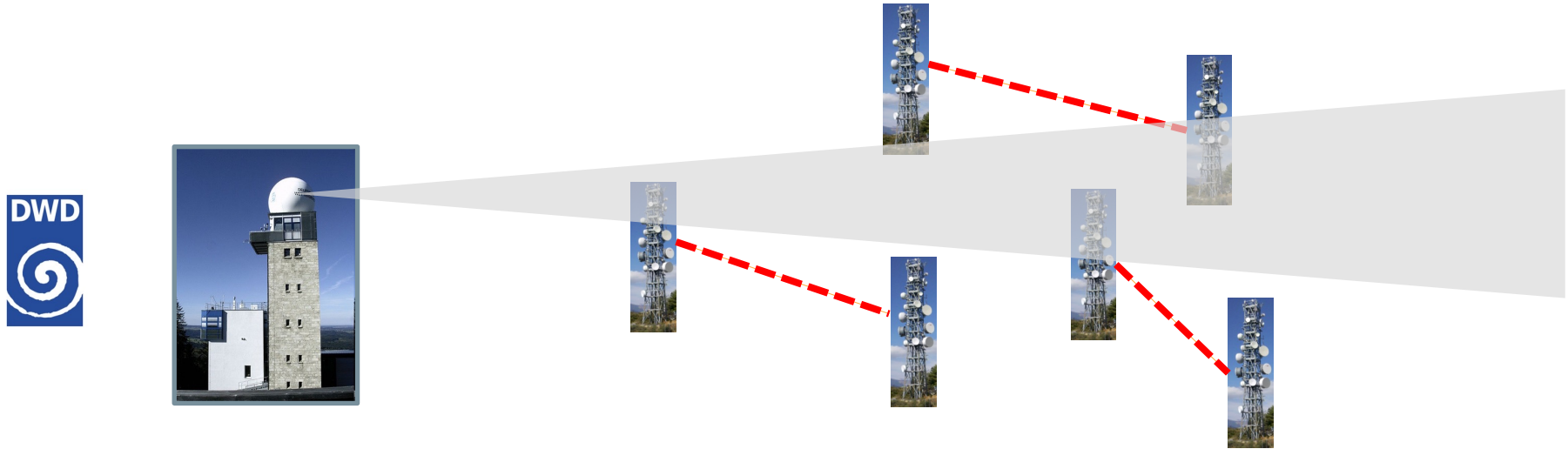
4b. CML-real-time

4. Real-time applications

4a. CML-radar combination

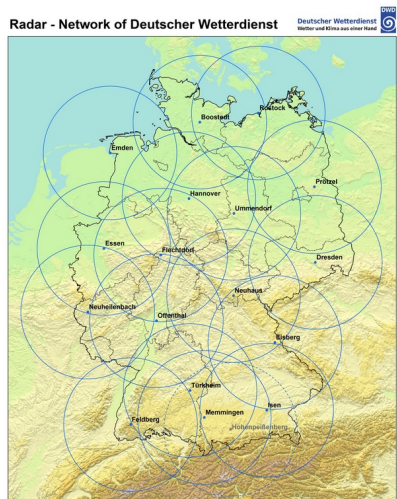
4b. CML-real-time

We use CMLs as additional rainfall information in the RADOLAN radar-rain-gauge adjustment

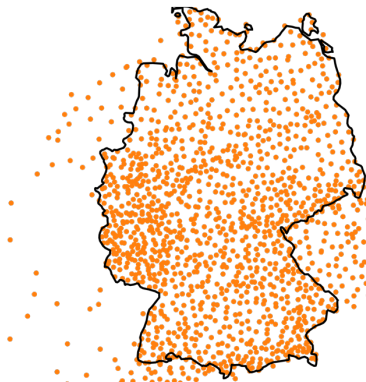


We produce two different adjusted radar products

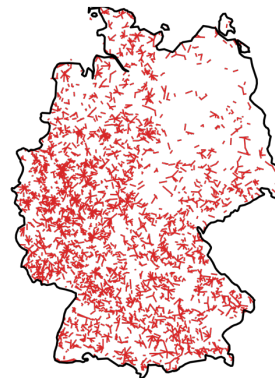
DWD radar network



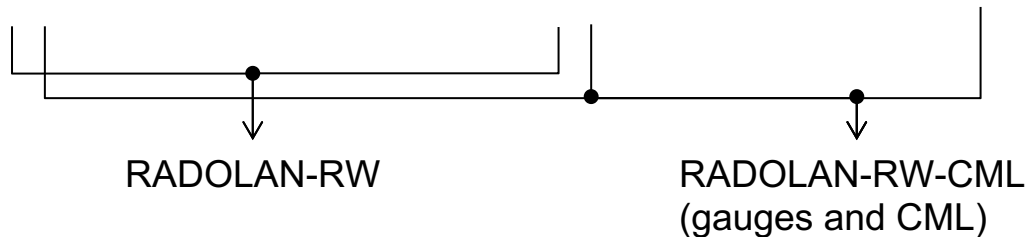
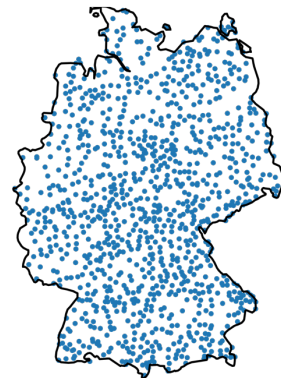
Automatic rain gauges
from DWD and
neighboring countries



4000 commercial
microwave links
(CMLs)



Manual rain gauges
from DWD with daily
data



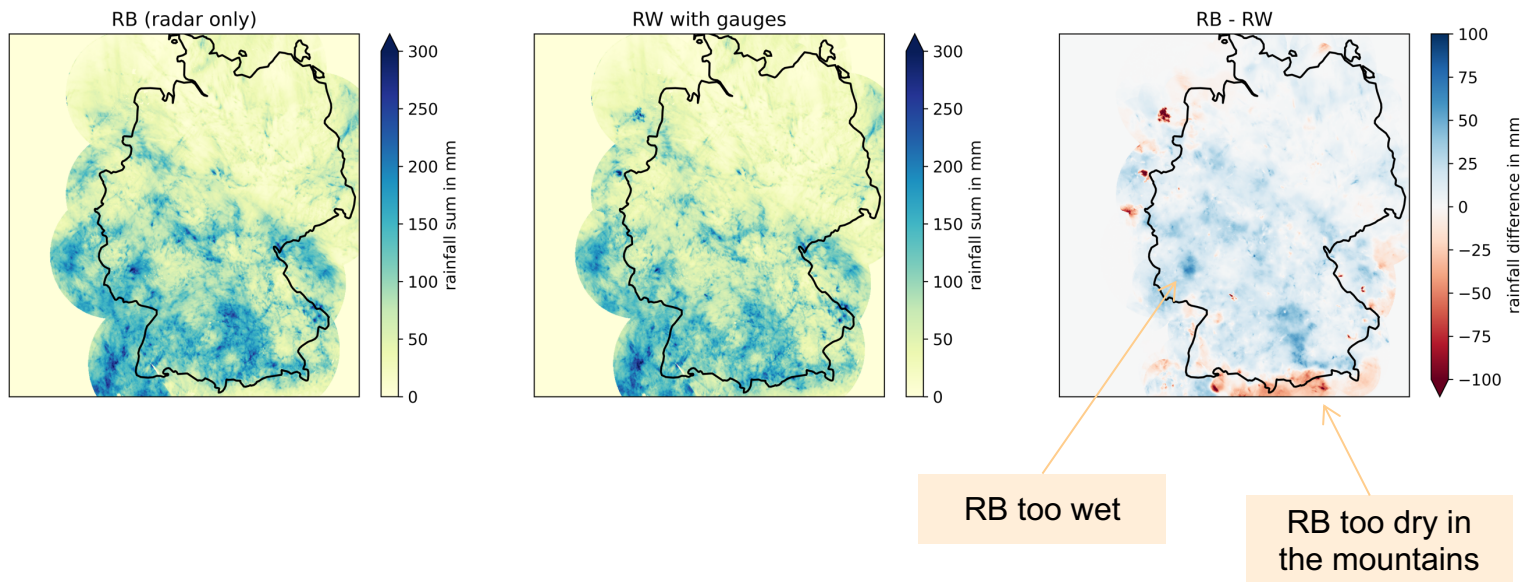
used as independent
validation data set

We use a Python implementation of the existing RADOLAN-RW gauge-adjustment routine

- CML rainfall information is integrated in the adjustment as path-averaged rain rate for each CMLs
- All RADOLAN-processing steps are implemented, except the final smoothing of the resulting rainfall field
- Fast execution time, approx. 30 seconds for one full adjustment run with 1500 gauges and 4000 CMLs, parallel executions of several time steps is possible using dask
- Built fully from open-source tools: wradlib, numpy, pandas, xarray, dask

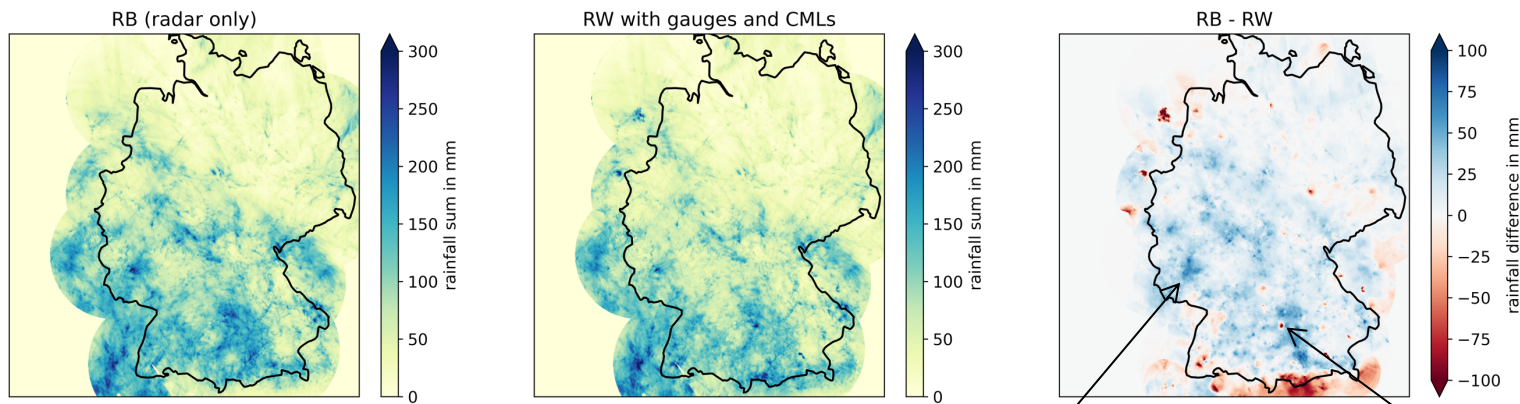
This are very first results for one month (May 2018)

- The monthly aggregation of the 1h-rainfall map (here for RADOLAN-RW with gauges only) looks as expected (validation on upcoming slides)



This are very first results for one month (May 2018)

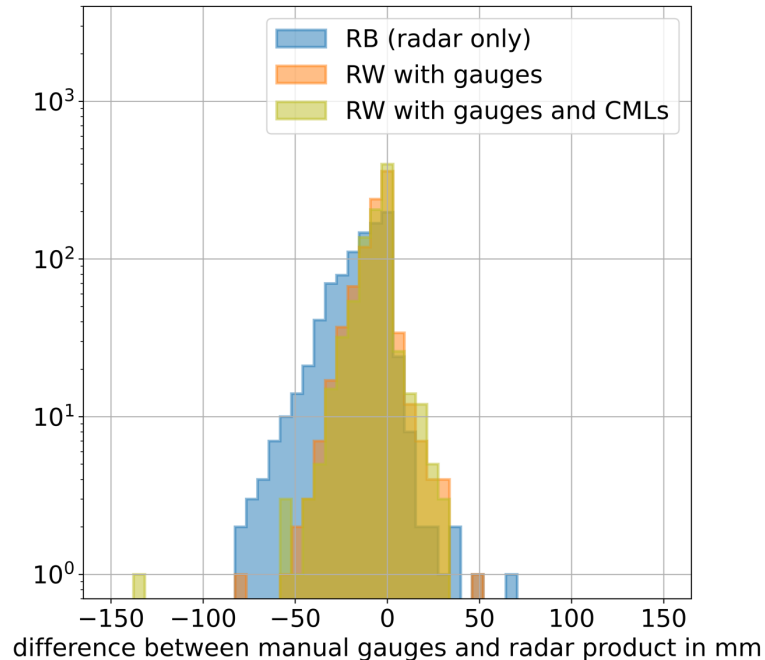
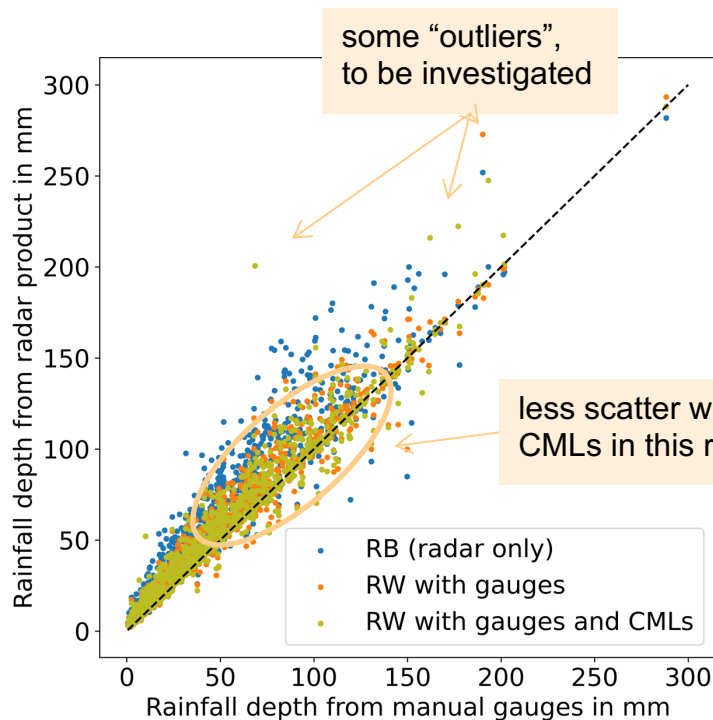
- With CMLs included, the general picture stays the same, with a slightly dryer adjusted product and some more significant differences on the small scale



Similar adjustment than with “gauges only” but more spatial structure

Strong local adjustments could be cause by CML artifact (not yet investigated)

Adding CMLs shows small improvement for rainfall depth over one month using the manual gauges as reference



Note that the CMLs have not (yet) used any radar information to improve their processing, potentially increasing their data quality

Next steps

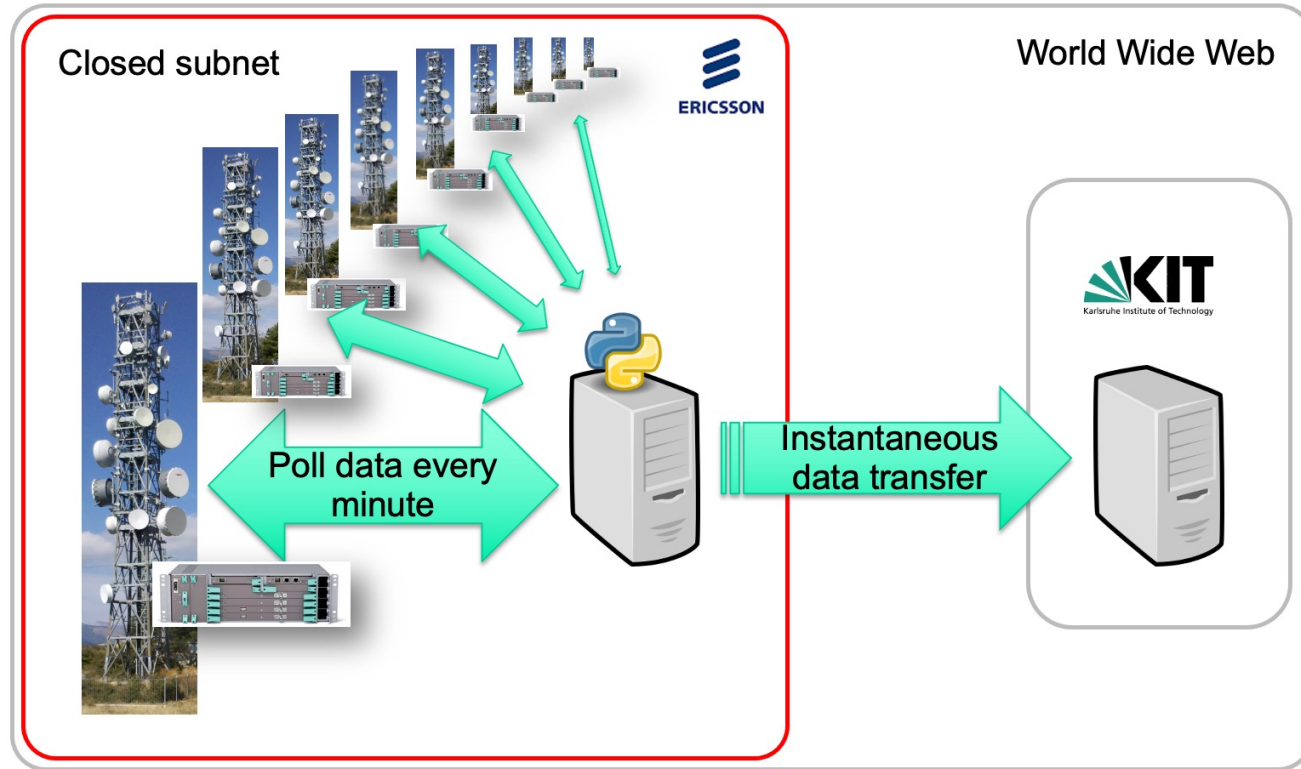
- Detailed analysis of effect of CMLs
- Use radar information to detect erratic CML fluctuation and to improve CML data quality
- Use real-time CML data to do RADOLAN-RW adjustment with CMLs continuously
- Investigate potential of radar adjustment with path-averaged CML observations for higher temporal resolutions (5-minutes or 15-minute)

4. Real-time applications

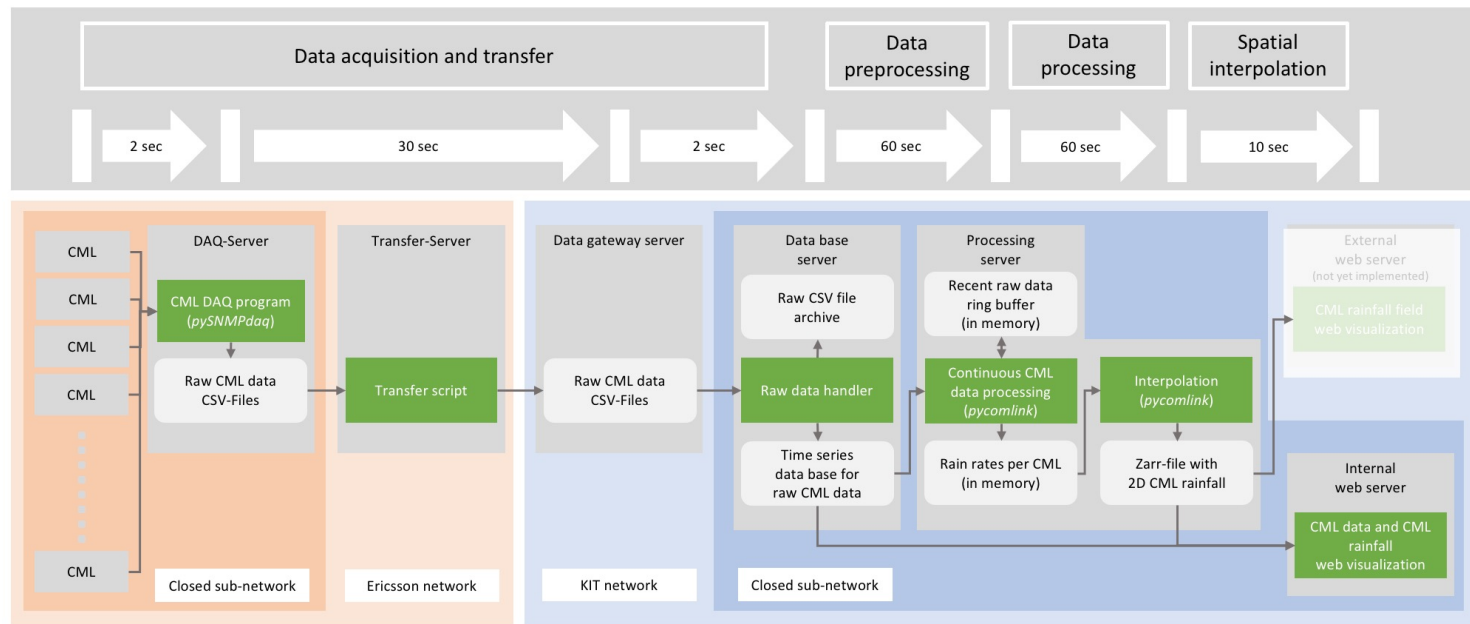
4a. CML-radar combination

4b. CML-real-time

We receive CML data in real-time



We can derived rainfall maps with 5-minute delay using our newest CML-processing with a CNN



The challenge is to keep the recent data of 1 day of CML data in memory for 4000 CMLs, because CML processing requires “knowledge” of past time steps

Acknowledgments



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References

Chwala, C. and Kunstmann, H.: Commercial microwave link networks for rainfall observation: Assessment of the current status and future challenges, 2019, Wiley Interdisciplinary Reviews: Water, 6, e1337, 2019.

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Graf, M., Chwala, C., Polz, J., and Kunstmann, H.: Rainfall estimation from a German-wide commercial microwave link network: Optimized processing and validation for one year of data, Hydrol. Earth Syst. Sci. Discuss., [accepted for publication], 2020. <https://www.hydrol-earth-syst-sci-discuss.net/hess-2019-423/>

Polz, J., Chwala, C., Graf, M., and Kunstmann, H.: Rain event detection in commercial microwave link attenuation data using convolutional neural networks, Atmos. Meas. Tech. Discuss., in review, 2019. <https://www.atmos-meas-tech-discuss.net/amt-2019-412/>