

D2.4 Report documenting benchmark algorithms on fast processing and quality control suitable for operational use

Version 1.0

Working Group	WG2
Deliverable	D2.4
Date	04/06/2025
Version	1.0
Author	Christian Chwala
Reviewer	Aart Overeem

Description	This deliverable is a report in the form of a paper, existing as a final draft at the time of writing, that summarizes the intercomparison of processing and quality control methods for OS data with a focus on CML-related methods.
Keywords	software, methods, benchmark

About OPENSENSE (COST Action CA20136). OPENSENSE brings together scientists investigating different opportunistic sensors (e.g. microwave links, citizen science), experts from weather services, and end-users of rainfall products to build a worldwide reference opportunistic sensing community. The overarching goals of the COST are to overcome key barriers preventing data exchange and acceptance as hydrometeorological observations, define standards to allow for large-scale benchmarking of opportunistic sensing precipitation products and develop new methods for precipitation retrieval, coordinate integration of the opportunistic observations into traditional monitoring networks, and identify potential new sources of precipitation observations. Further details can be found [here](#):

Table of contents

1. Overview of WG2 tasks and synchronisation with D2.4	4
2. Software repository in GitHub with method intercomparison	4
3. Paper draft with results of method intercomparison	6

Glossary

WG	Working Group
MoU	Memorandum of Understanding
OS	Opportunistic Sensors
CML	Commercial Microwave Link
PWS	Personal Weather Station
SML	Satellite Microwave Link

D2.4 Report documenting benchmark algorithms on fast processing and quality control suitable for operational use

1. Overview of WG2 tasks and synchronisation with D2.4

This document reports on the official OpenSense deliverable D2.4, which is part of the activities carried out by WG2. The activities started in the grant period (GP2) and continued into GP3. The analysis was mostly during GP2, but the final report in the form of a paper was postponed to GP4.

D2.4 is the result of WG2's work on the homogenization of processing methods and the corresponding software tools, reporting on the performance of individual methods. It builds on the work done for D2.3 and the follow-up work, which has resulted in the joint development of three software packages, which will be finalised in the first stable versions for D2.5. These WG2 activities and deliverables are shown in Table 1.

Table 1. A timetable of WG2 activities and deliverables. Note that D2.4 was postponed to GP4 from the original due date Q1 in GP3.

	year 1				year 2				year 3				year 4			
	Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4
WG2 - Activities for:																
Software development				d21			d23									d25
OS processing methods									d24							
PhD&ECI Training School					d22											

D2.1 - Guidelines for contributing to Git repository

D2.2 - Content for training school on OS processing published at website

D2.3 - First release of community software package with processing and quality control algorithms

D2.4 - Report documenting benchmark algorithms

D2.5 - New release of OS processing package

2. Software repository in GitHub with method intercomparison

To carry out the method intercomparison, we created an open software repository in the OpenSense GitHub group. This repository holds reproducible Jupyter notebooks to carry out all preparation and processing steps to produce the results that are part of the paper that summarises this analysis.

The analysis focuses on the intercomparison of CML wet-dry classification and CML wet antenna attenuation correction methods. It uses fully open-source implementations from the pycomlink

D2.4 Report documenting benchmark algorithms on fast processing and quality control suitable for operational use

software package, which was extended via WG2 work for this task, and two large open datasets with CML, rain gauge and radar data. Namely, these datasets are the OpenMRG dataset from Gothenburg in Sweden and the OpenRainER dataset from the Emilia-Romagna region in northern Italy.

The repository is located at https://github.com/OpenSenseAction/cml_method_benchmarking. Figure 1 gives a brief impression of the repository. Further details can be explored directly there since all relevant information is contained in the Jupyter notebooks. The results are currently being summarised in a paper, which is described in the next section.

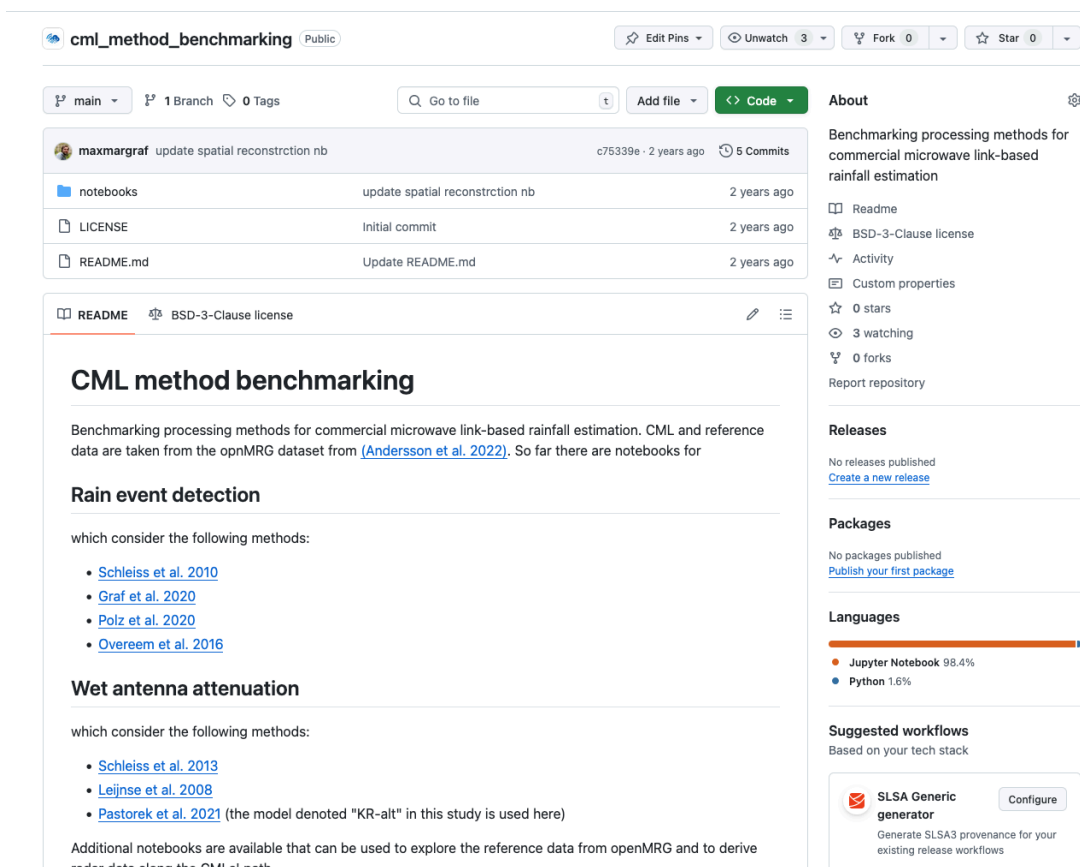


Figure 1: Main page of the GitHub repository for the method intercomparison with basic info on the provided methods. The notebooks where the analysis is done are in the respective subdirectory.

3. Paper draft with results of method intercomparison

The results of the method intercomparison are summarised in a paper, which is currently in the final drafting stage and is being reviewed by WG2 members. Due to the limited capacity of WG2 members, the finalisation of the paper had to be postponed to the end of GP4. Here we provide a brief summary of the results.

There is no clear best method for wet-dry classification, but we can give recommendations based on the properties of a CML dataset. For dense CML networks with either 15-minute min-max sampling or sub-minute instantaneous sampling, the nearby-link method (O_{red}) is recommended. It will provide results with very few false positives (FP) and relatively many false negatives (FN), with an overall high performance as long as there are at least 3 sublinks within a radius of 15 km, otherwise this selected sublink and time interval will not be classified and is not used in the evaluation. Independent of the network density, the two data-driven methods based on neural network pattern recognition in the CML time series (\emptyset_{red} and P_{red}) should be used when the CML data is derived with 1-minute instantaneous sampling. An overview of the wet-dry classification results for the OpenMRG dataset is given in Fig. 2 and for OpenRainER in Fig. 3.

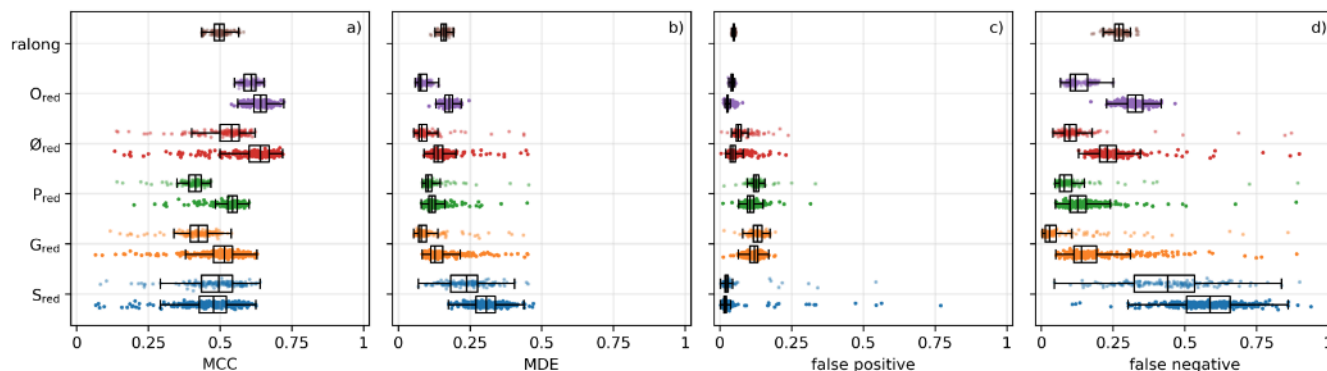


Figure 2: Binary evaluation of five rain event detection methods for the openMRG dataset. Each colour indicates one method. The upper, lighter points and boxplot show the metric for rain gauges as a reference (within two km of a CML), and the lower, darker points and boxplot show the metric for ralong (here, radar data) as a reference. Additionally, using the path-average radar for wet-dry classification, shown as ralong, is compared to the rain gauges used as reference. MCC is the Matthews Correlation Coefficient and MDE is the Mean Detection Error.

D2.4 Report documenting benchmark algorithms on fast processing and quality control suitable for operational use

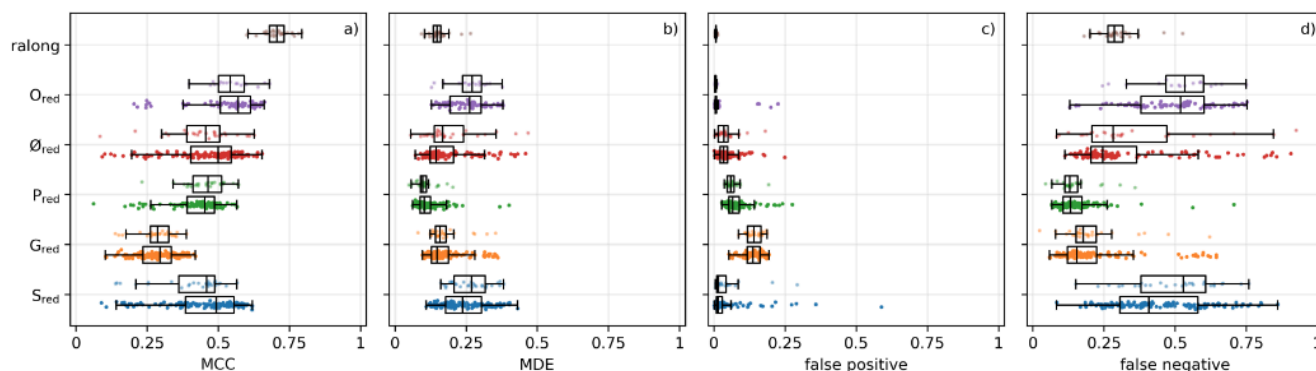


Figure 3: Binary evaluation of five rain event detection methods for the OpenRainER dataset. Each colour indicates one method. The upper, lighter points and boxplot show the metric for rain gauges as a reference (within two km of a CML), and the lower, darker points and boxplot show the metric for ralong (here, gauge-adjusted radar data) as a reference. Additionally, using the path-average radar for wet-dry classification, shown as ralong, is compared to the rain gauges used as reference. MCC is the Matthews Correlation Coefficient and MDE is the Mean Detection Error.

We compared the WAA (wet antenna attenuation) correction methods based on their median bias and the spread of bias for all CMLs. The used method heavily influences the median bias, as well as the spread of biases. This is driven by the robustness of a method to handle both different rain events and CML properties like frequency and length. We recommend the method from Pastorek (P_{waa}), even if it showed an underestimation when using the originally proposed parameters and has a stronger median bias than some of the other methods. However, the spread of biases is (much) smaller for P_{waa} compared to the other methods. Results are shown in Figure 4 for both the OpenMRG and the OpenRainER datasets.

D2.4 Report documenting benchmark algorithms on fast processing and quality control suitable for operational use

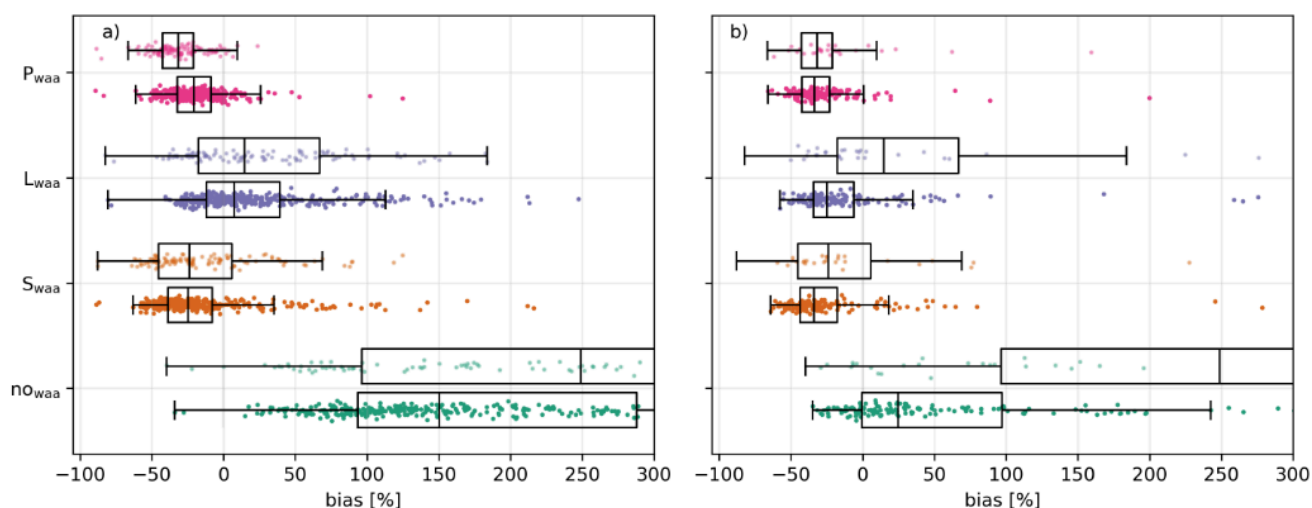


Figure 4: Bias of WAA correction models for the a) OpenMRG and b) OpenRainER dataset compared to rain gauge and radar reference (radar data for OpenMRG and gauge-adjusted radar data for OpenRainER) at 15-minute temporal resolution. Each method is evaluated with rain gauges within a 2 km radius around each CML, shown by the respective upper boxplots with lighter colored points and with the radar reference intersected along the CMLs' paths along shown by the respective lower boxplots with darker colours.