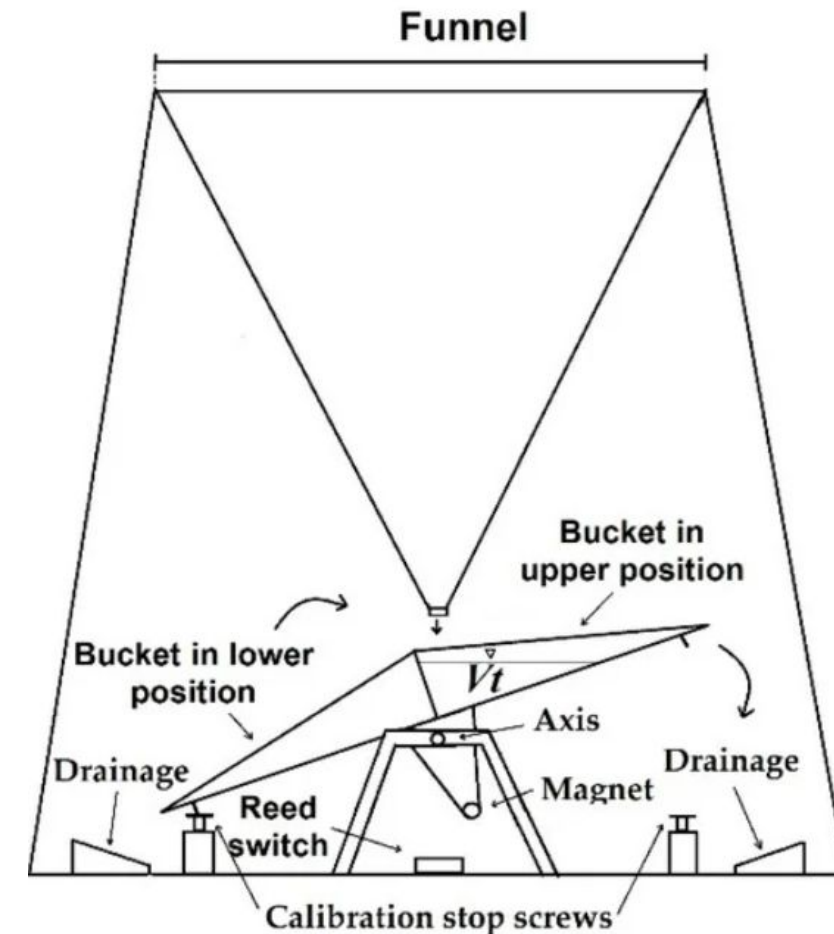


Overview and comparison of three quality control algorithms for rainfall data from personal automated weather stations (PWS)

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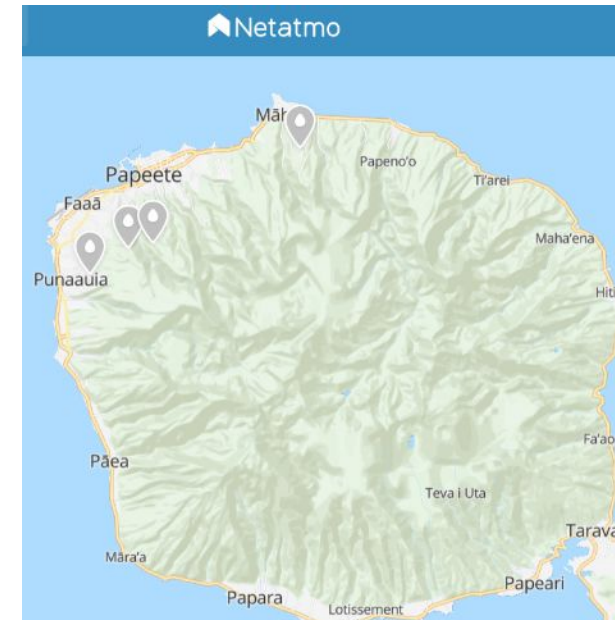
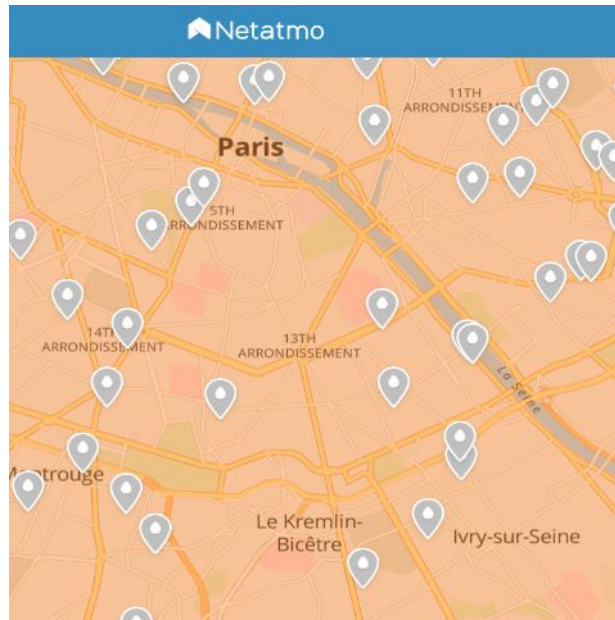
What is a tipping bucket rain gauge?

The tiniest “bucket” in the world!



Where are these tiny buckets?

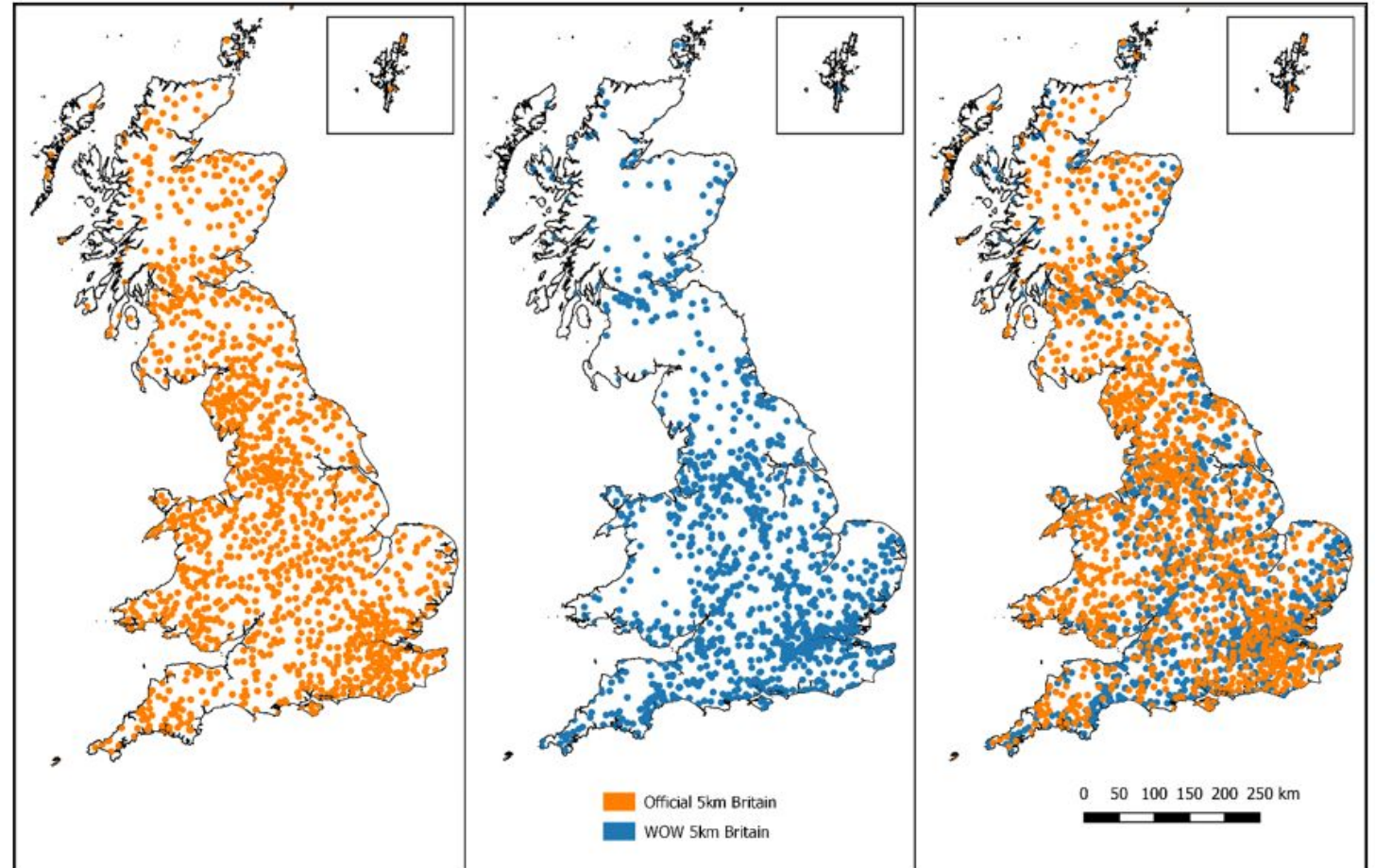
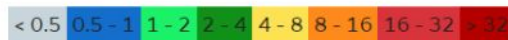
They get everywhere, from Paris to Papeete...



PWS offer an amazing opportunity to obtain a higher spatial resolution rainfall data set.



Rainfall Rate (mm/hr)



But are the data any good?

Yes, and no.

Unlike official monitoring, the rain gauges *may* not have been installed following WMO Guidelines.

But they can be operated by people who take monitoring very seriously indeed.



Schoolboy train-spotters at Newcastle Station, August 1950.

© National Railway Museum / SSPL

So, we need quality control?

- Statistical quality control is focused on the output data.
- After meeting via the OpenSense network researchers from Germany, the Netherlands and the UK decided to compare notes on QC methods.
- We wrote a ***Technical Note: A guide to using three open-source quality control algorithms for rainfall data from personal weather stations.***
- We used rainfall data from Amsterdam as a case study.

What does the QC do?

1. PWSQC (Netherlands) - Uses a series of neighbour checks to filter and bias correct rainfall.
2. PWS-pyQC (Germany) – Correlates against reference network then bias corrects and filters erroneous rainfall.
3. GSDR-QC (UK) – Flags suspicious observations against user defined thresholds and neighbour and/or climate indices checks then removes erroneous rainfall.

| | PWSQC | PWS-pyQC | GSDR-QC Local |
|--------------------------------|--|--|---|
| QC modules | <ol style="list-style-type: none"> 1. Neighbour selection 2. Faulty Zeroes & High Influx filter 3. Station Outlier filter & bias correction factor determination | <ol style="list-style-type: none"> 1. Indicator based filter 2. Bias correction 3. Event based filter | <ol style="list-style-type: none"> 1. Flagging of suspicious observations using defined rule base 2. Filtering of suspicious observations not meeting QC criteria |
| Reference dataset required | No, but optional part of initialization of bias correction factor determination | Yes, required for 1, 2 and 3 | Yes, ETCCDI data plus user defined maximum daily and hourly thresholds |
| Programming language | R | Python | Python |
| Ground truth used in method | Median values from neighbouring PWS | PWS should fit in space-time dependence structure of reference data | Neighbouring gauges are compared to each other and optionally against a reference dataset |
| Level of QC-allocation | - Per measurement | <ul style="list-style-type: none"> - Per full PWS time series - Event based | <ul style="list-style-type: none"> - Per individual measurement - Dynamic nature is suitable for longer time series |
| Output after running QC method | <ul style="list-style-type: none"> - Original PWS dataset - 3 flag files conveying flag attribution to individual observations for all three QC - 1 file with bias correction factors generated for each observation - Bias adjusted PWS dataset with only reliable observations | <ul style="list-style-type: none"> - Set of trustworthy PWS - Individual bias correction for each time series - Implausible time intervals removed for each time series | <ul style="list-style-type: none"> - Flag file for each gauge showing individual test results - Output file with reliable observations |

Which algorithm is the best?

That depends, they each have their strengths...



| Applicability regarding | PWSQC | PWS-pyQC | GSDR-QC Local |
|--|---|--|---|
| Temporal scale | HI-filter has no lead-up time, but (with default parameters) FZ filter requires 30 min and SO-filter and bias correction require ≥ 2 weeks of data with > 100 nonzero intervals. Most suitable for long periods of continuous data. | Time series should be long enough to include significant number of rain events, which is dependent on the climatic region and temporal resolution. | Where neighbouring PWS are available within 50 km there is a minimum requirement of 1 year of overlapping data. Otherwise, where climate indices are available 1 month minimum of data is required. |
| Spatial scale | Network can span large areas, provided that neighbour PWS values are a good proxy of the ground truth throughout the network. Neighbours are defined by a range around a station which assumes climatological agreement with neighbours in all directions | Due to need for reference set, PWS network has to overlap with reference network. For the indicator filter, the data from the reference network needs to represent the local spatial and temporal rainfall variability, but a temporal overlap is not necessary. | There are no limitations to the spatial scale. Consideration must be given that the same daily and hourly maximum rainfall thresholds are applied on the whole area. |
| Temporal resolution | 5 minute timesteps (or longer) | 1 hour timesteps (or longer) | 1 hour timesteps (or longer) |
| Spatial resolution | Due to neighbour checks, most suitable for dense networks | Applicable for both dense and sparse networks | Applicable for both dense and sparse networks |
| Operational potential | Current version of code works only on static dataset, but theory applies for operational application | Current version of code works only on static dataset, but theory applies for operational application | Developed for static datasets |
| Approximated runtime for Amsterdam PWS dataset | 1. Neighbour selection: flash 2. FZ and HI filter: lunch break 3. SO and bias correction: weekend | 1. Indicator correlation: flash 2. Bias correction: lunch break 3. Event Filter: coffee time | 1. Create gauge objects: flash 2. Run QC: coffee time 3. Extract QC summary: flash |
| Impact of PWS network scaling on run time | As whole network needs to be evaluated for each timestep, large dependency on number of stations | Calculation of distance matrices increases nonlinear with number of stations | Linear with number of PWS |

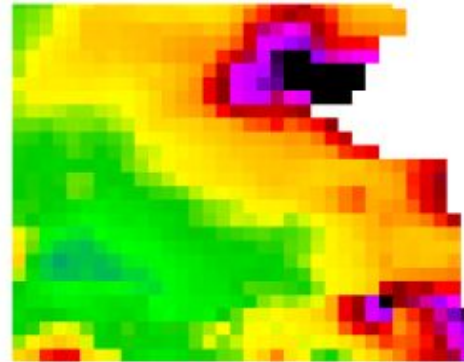
Show me some results!

a) gauge adjusted radar accumulation

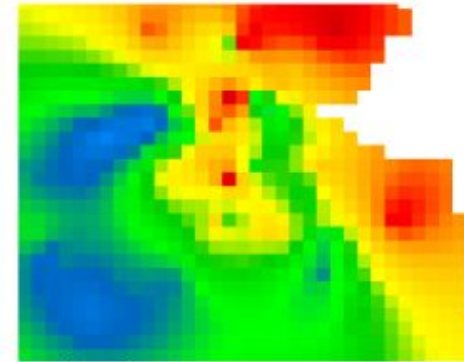
b), c) & d) post QC interpolated PWS accumulations

e) gauge locations

a) Radar reference

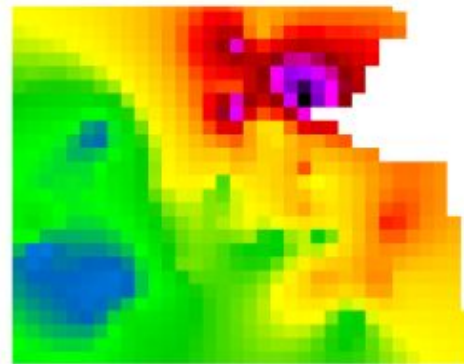


b) PWSQC



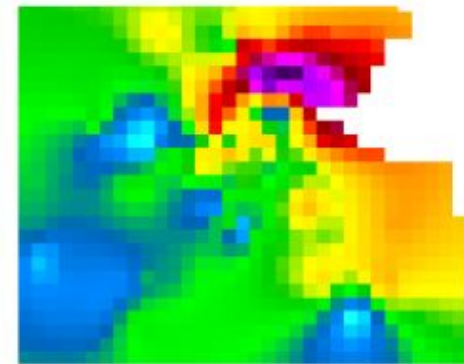
Number of PWS:
min=70, mean= 83, max= 90

c) PWS-pyQC



Number of PWS:
min=30, mean= 65, max= 71

d) GSDR-QC



Number of PWS:
min=96, mean= 97, max= 99

e) Study area and PWS locations



It looks amazing, can I try it?

The gauge-adjusted radar product from the Royal Netherlands Meteorological Institute (KNMI):

<https://dataplatfom.knmi.nl/dataset/rad-nl25-rac-mfbs-5min-netcdf4-2-0>

PWS dataset: <https://doi.org/10.1029/2019GL083731>

All QC software is open source and can be accessed in the OpenSense sandbox:

https://github.com/OpenSenseAction/OPENSENSE_sandbox

And who will help me?

Abbas El Hachem

Jochen Seidel -

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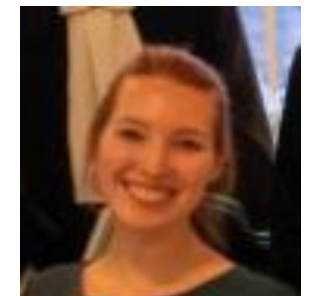
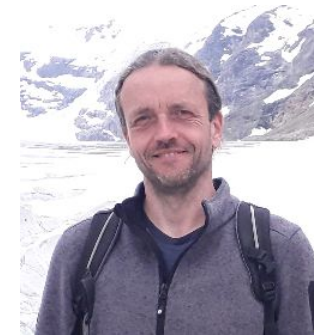
Roberto Villalobos Herrera

Aart Overeem

Remko Uijlenhoet

András Bárdossy

Lotte de Vos - lotte.de.vos@knmi.nl



Is there anything else I should know?

Probably too much to mention here... but happy to answer any questions.

