



**CT6 - Benchmark on methodologies to
integrate low-cost sensor networks with
official measurements and modelled data;
Status and first results**

- At the FAIRMODE meeting in Berlin (2020) the topic of sensor networks was discussed. It was decided to include this topic in the road map for the next years as a “Benchmarking” topic. The Benchmarking stage is intended as a first step that aims at exploring and comparing results from different approaches, in this case of using/exploiting sensor networks.
- The FAIRMODE road map describes Benchmarking as:

“This stage also requires developing and testing a standardized evaluation or inter-comparison methodology (possibly supported by common tools and common datasets) for collecting and reporting model inputs and outputs in a way that enables relevant comparisons.”

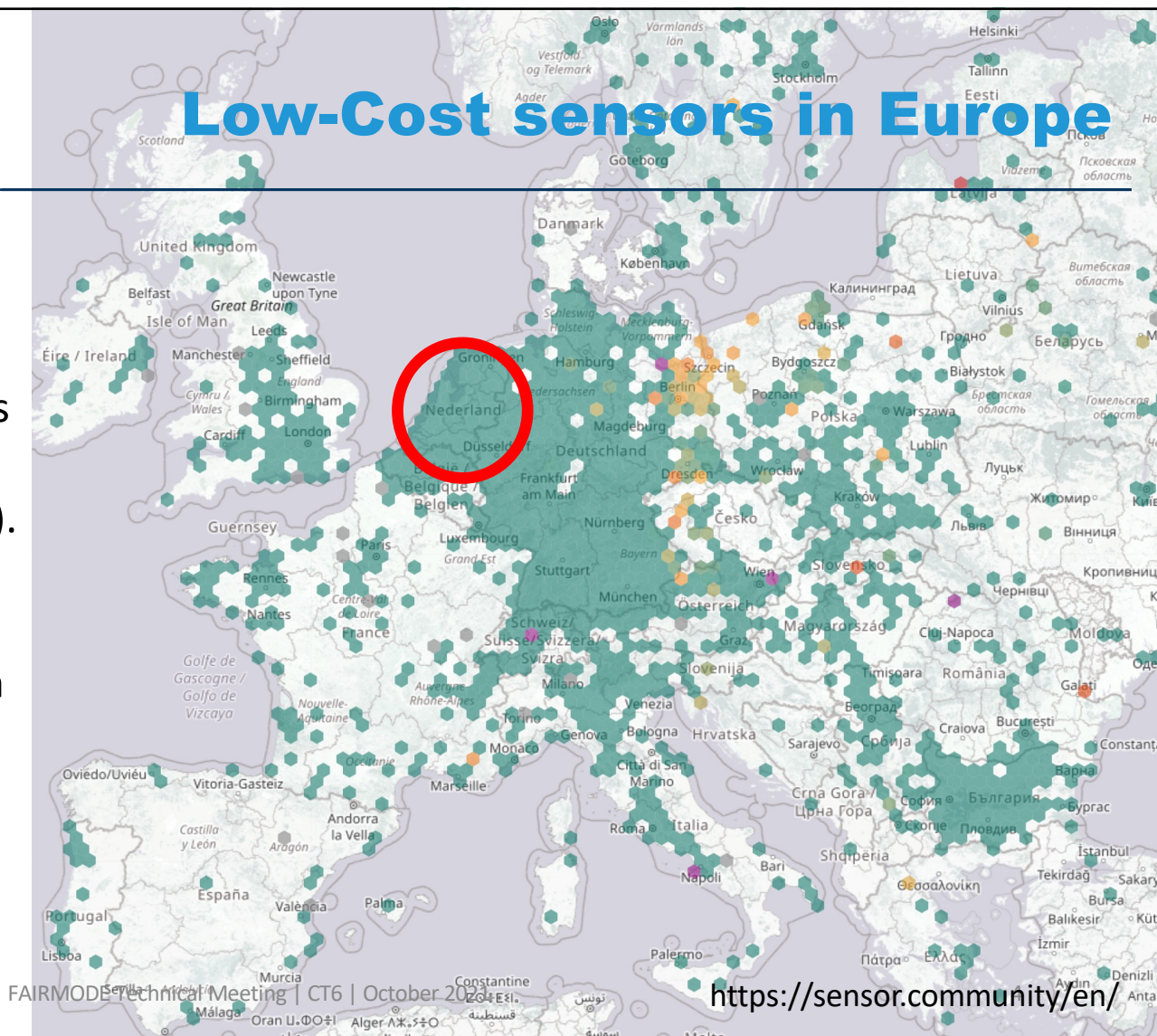


- Initially, two parallel benchmarks were foreseen, PM_{2.5} and NO₂.
- Uncertainties of low-cost NO₂ sensors larger than for many types of PM_{2.5} sensors.
- In Europe not that many NO₂ sensors in operation → no network approach possible.
- Fusion/assimilation of NO₂ sensor data is more of a challenge.
- So, it was decided to start with PM_{2.5} and work on NO₂ after that.

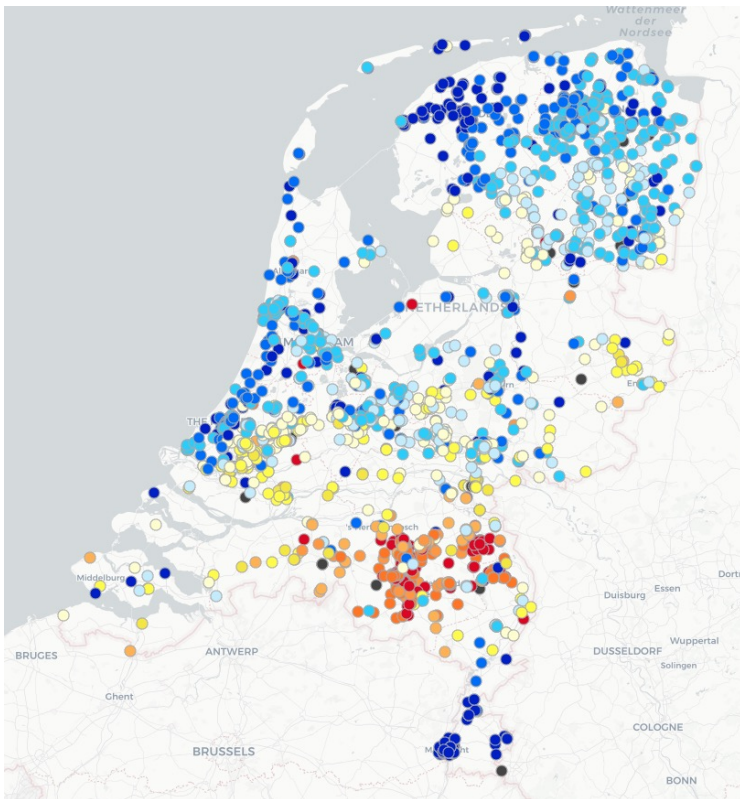


Low-Cost sensors in Europe

- Several PM_{xx} sensor networks are operational in Europe.
- Biggest citizen driven network is the German Sensor.Community (<https://sensor.community/en/>).
- Start benchmark with real sensor data that are available in the Netherlands, both citizen science and from professional projects.
<https://sensors.rivm.nl/>



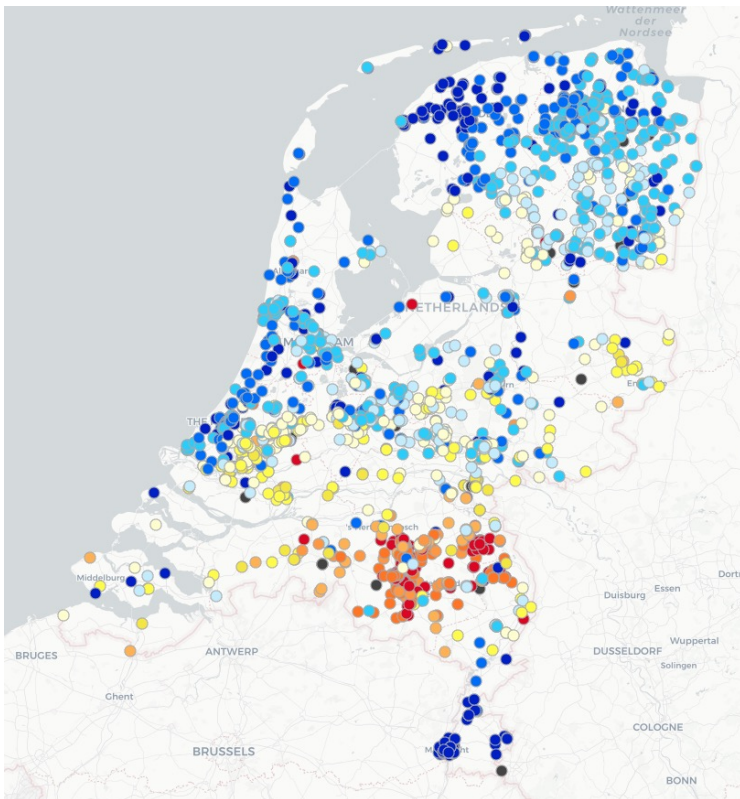
Low-Cost sensors benchmarking



- Use data from low-cost sensors ($\sim 25\text{€}/30\text{\$}$) in the Netherlands providing $\text{PM}_{2.5}$, mostly Nova SDS-011.
- Since January 2021, hourly sensor data, official data and model results provided to participants on real-time basis.
- All interested FAIRMODE participants can use these data to work on:
 - Selection and calibration of sensors;
 - Individual sensors / network;
 - Data fusion/assimilation.

<https://sensors.rivm.nl/>

Low-Cost sensors benchmarking



- A group of active participants has met several times since October 2021, roughly once every two months.
- Different approaches on calibration and data fusion were presented and discussed.
- **New participants still welcome!**

<https://sensors.rivm.nl/>

In the Netherlands enough sensors (presently ~1900), other measurements (~ 45) and model results available for several different calibration strategies:

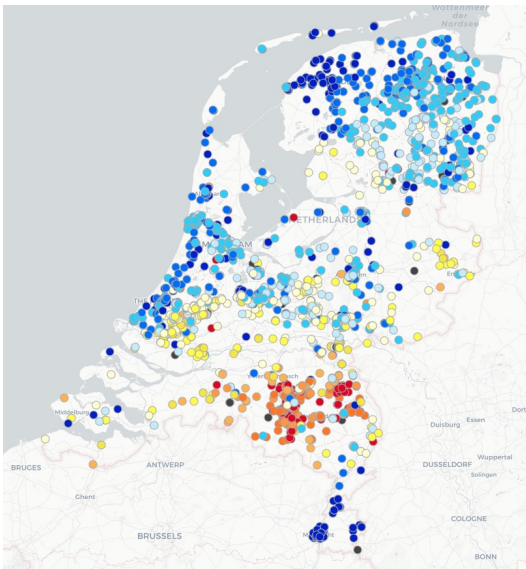
Use of sensor data

- Focus on average spatiotemporal patterns.
- Focus on patterns in hyper-local concentrations. (i.e. woodburning)

Raw sensor data ↔ Full network calibration

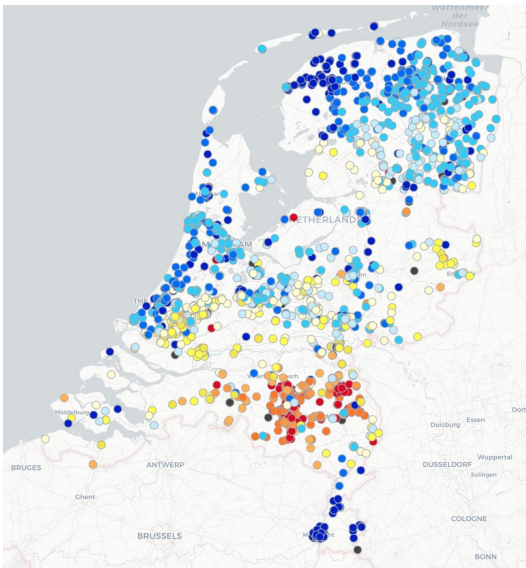
Level	Name	Definition
0	Raw measurements	Original measurand produced by sensor system
1	Intermediate geophysical quantities	Estimate derived from corresponding Level-0 data, using basic physical principles or simple calibration equations, and no compensation schemes.
2A	Standard geophysical quantities	Estimate using sensor plus other on-board sensors demonstrated as appropriate for artifact correction and directly related to measurement principle (Hagler et al., 2018)
2B	Standard geophysical quantities-extended	As Level-2A but using external data demonstrated as appropriate for artifact correction and directly related to measurement principle (Hagler et al., 2018)
3	Advanced geophysical quantities	Estimate using sensor plus internal/external inputs, not constrained to data proven as causes of measurement bias or related to measurement principle (Hagler et al., 2018)
4	Spatially continuous geophysical quantities	Spatially continuous maps derived from network of sensor systems

Toward a Unified Terminology of Processing Levels for Low-Cost Air-Quality Sensors, Philipp Schneider *et al.*, Environmental Science & Technology 2019 53 (15), 8485-8487



Starting from the same PM_{2.5} data set all participants use their own approaches and tools to get the optimal results for calibration and (eventually) data fusion.

- RIVM (NL), INERIS (FR), VITO (BE): network approach, data fusion of existing PM_{2.5} maps with cleaned-up/calibrated data.
- U. Aveiro (PT): AI/ ANN as tools to support future methodologies (is there enough data?)
- ISSeP (BE): Looking at selected sensors, close to official data.
- UC. Cork (IE): looking at correlations between groups of sensors.
- VMM (BE): look at hyper-local concentrations.
- Several parties looking at possibilities.



Friday 08/10 09:00 - 10:30

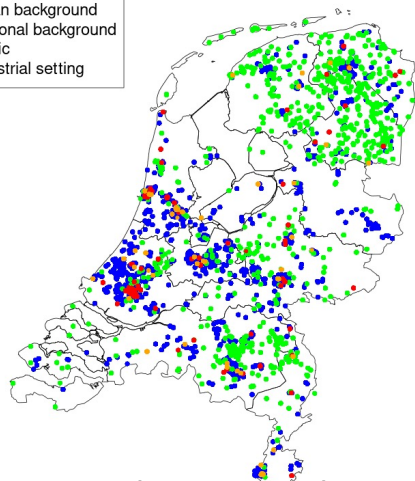
Detailed presentations CT6

- Near real time assessment with low-cost sensors, Alicia Gressent, INERIS
- Near real time assessment with low-cost sensors, Vera Rodrigues, U.Aveiro
- Near real time assessment with low-cost sensors, Pascal Joassin, ISSeP
- Data assimilation for PM2.5 RIO maps; Bayesian approach, Jorge Sousa, VITO
- Local sensor network in Cork City, Rosin Byrne, UC Cork

1. Outliers detection

Create categories of sensor observations depending on their typology, season, weekend days and weekdays, times of day. Apply outliers detection methodology based on confidence interval estimation (*van Zoest et al., 2018*).

- Urban background
- Regional background
- Traffic
- Industrial setting



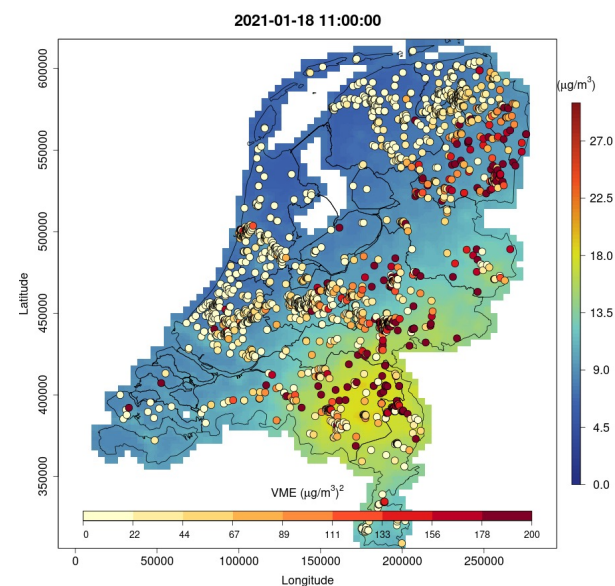
Estimated sensor typology.

2. Calibration

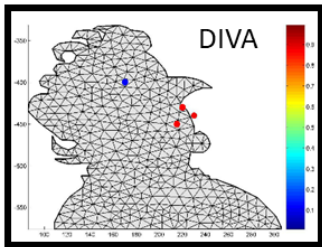
Look for sensors in the vicinity of the reference stations based on their representativeness that depends on the typology of the station, then estimate local correction factor and interpolation by kriging.

3. Data fusion

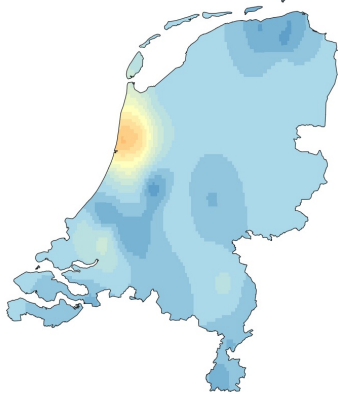
Apply SESAM (data fusion with **SEnSors for Air quality Mapping**) tool: fusion (universal kriging) of sensor data and official map considering data variability and uncertainties (VME, variance of measurement errors).



Official map in the background and VME as defined in SESAM.



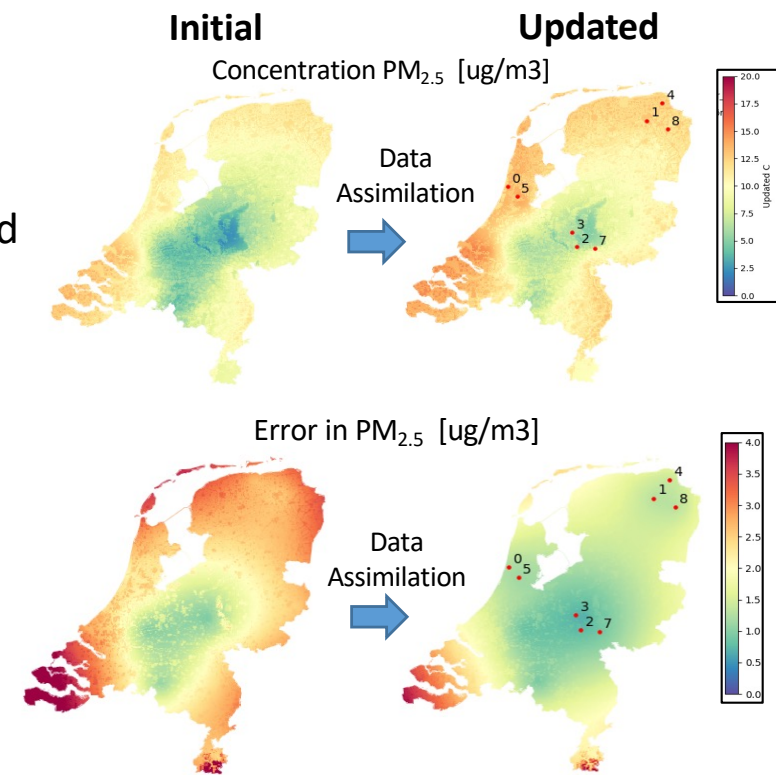
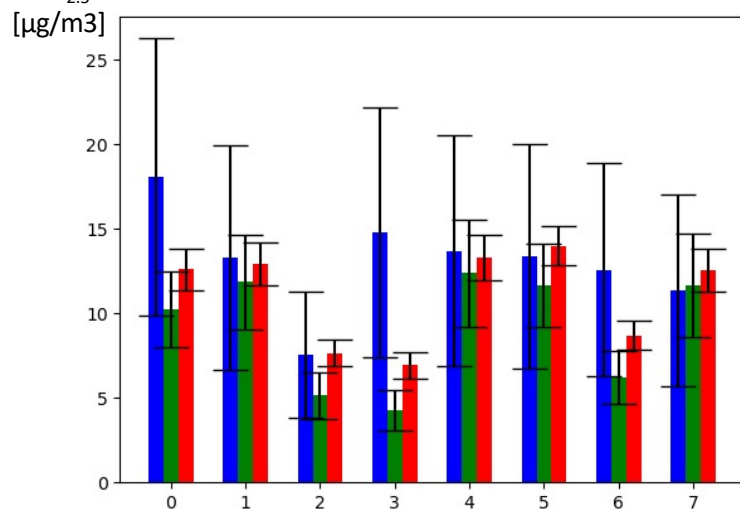
2021-05-16T12 – PM2.5



1. Measurements from reference stations are used to produce interpolated $[PM_{xx}]$ fields for the studied area. Interpolations are done using the DIVA tool (Data-Interpolating Variational Analysis - <https://github.com/gher-ulg/DIVA>) which associates an error field to each interpolated field.
2. Measurements from low-cost sensors are first selected considering a maximal acceptable value of the error field at the location of the sensor. Selected sensor measurements are compared to co-located interpolated reference values, showing the deviations of the sensor during the measurement.
3. Deviations of each sensor are plotted with their corresponding reference values showing a typical $Reference = A \times Sensor + B$ relation where slope A and intercept B are correcting parameters of the sensor. Measurements of relative humidity are used to create subsets of the correcting parameters. Next, low-cost sensors are selected considering quality criteria for slopes and intercepts.
4. An iterative approach is finally applied as the correctable low-cost sensors are recombined with the official data in order to enlarge the initial set of reference sources, starting a new calibration.
5. For any moment of interest, low-cost sensor values are corrected using linear parameters. Only corrected sensor data are combined with official data, producing final interpolated $[PM_{xx}]$ fields.

- Developing data assimilation approach based on a Bayesian approach (Kalman Filter)
- Methodology updates concentration and uncertainty values of the updated map
- Fusion is balanced according to both measurement and model error

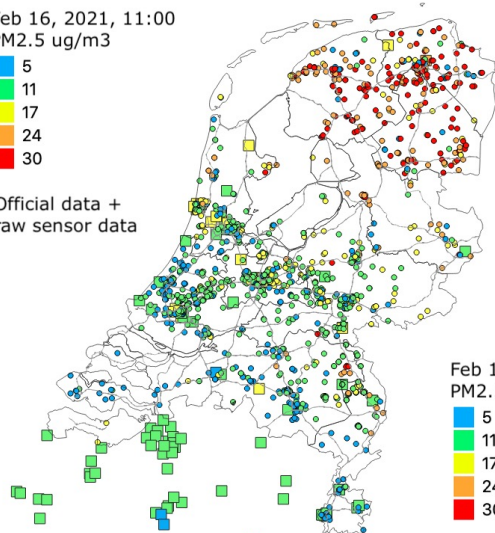
PM_{2.5} Observed, Predicted and updated values at stations



Feb 16, 2021, 11:00
PM2.5 ug/m3



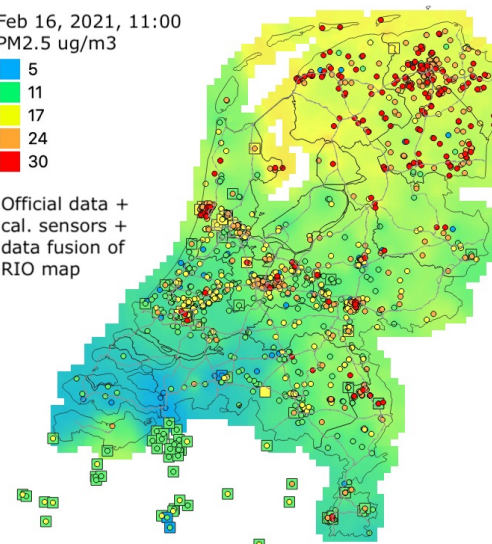
Official data +
raw sensor data



Feb 16, 2021, 11:00
PM2.5 ug/m3

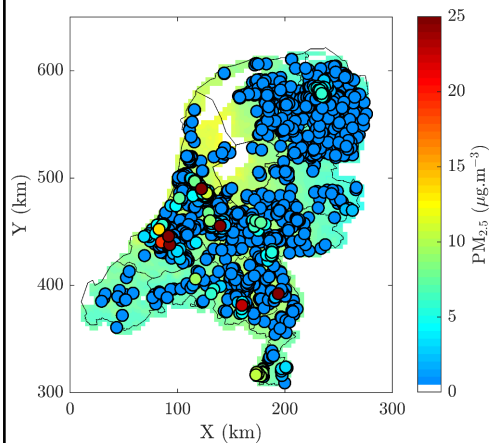


Official data +
cal. sensors +
data fusion of
RIO map



- Low-cost PM_{2.5} sensors are sensitive to humidity. Built-in low-cost T / RH sensors often break down.
- In the Netherlands a “Network” approach is used:
 1. Identify groups of sensors around official measurement locations, determine the ratio between those values and the average of the sensors → local “correction factors”.
 2. Interpolate the correction factors for all locations in the Netherlands.
 3. Bootstrap to estimate the uncertainties.
 4. Data fusion of calibrated sensors and “official” PM_{2.5} map using variance weighting.

An R tool implementing the RIVM approach was provided for all benchmark participants.



University of Aveiro (PT), Sensor data calibration

Assess the temporal profile of the calibration factor of each sensor.

Use type of location, land use, traffic data, meteo, ...

AI/ ANN as tools to support future methodologies (do we have enough data?)

University College Cork (IE)

Classification (location wrt official measurement location).

Clustering of patterns in sensors.

Take recent behavior (few hours) of sensors into account.

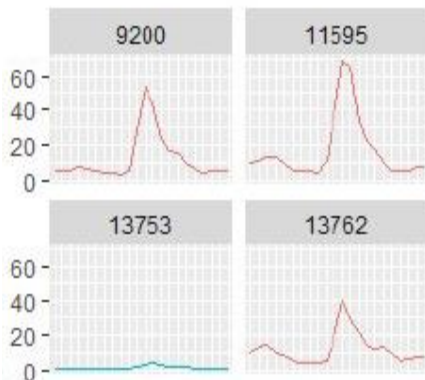
VMM (BE), Local approaches

Validation/calibration of sensor signals → “how to select the good ones?”.

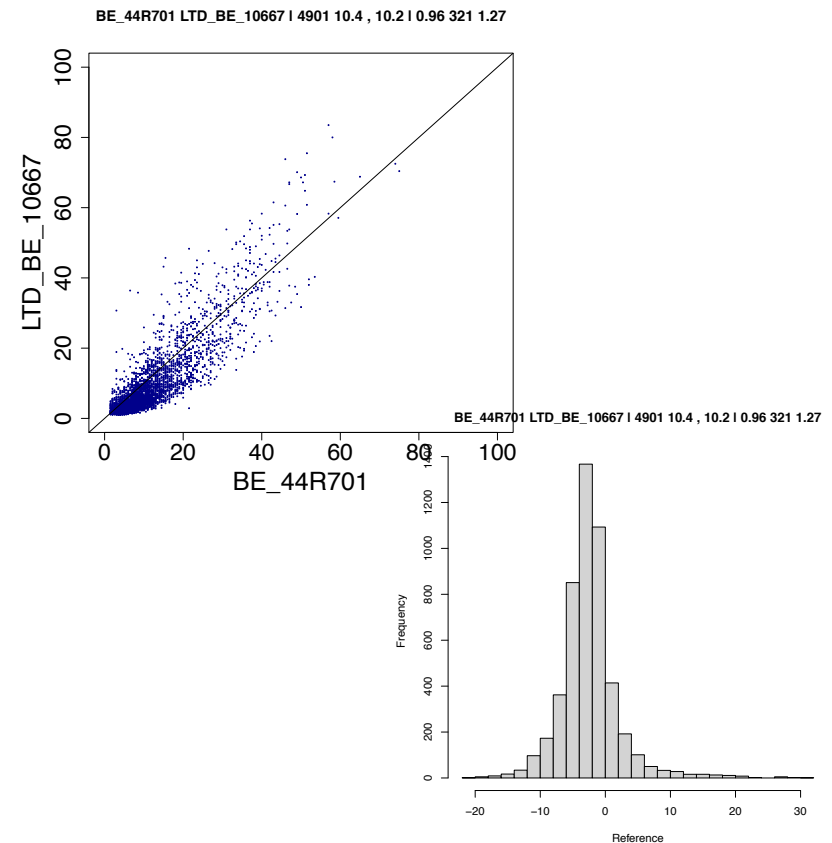
Auto-peak detection local phenomena + clustering.

Integration of local phenomena (i.e. wood burning) in air quality model maps (with **VITO**) for PM_{2.5}.

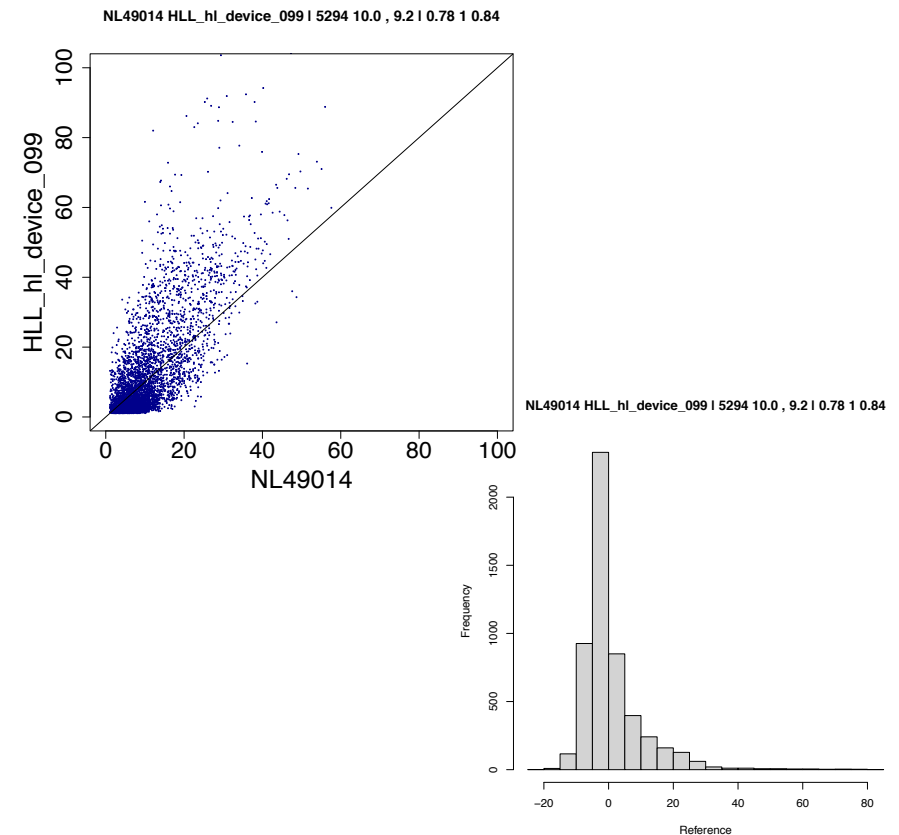
Other approaches being developed ...



- The initial steps of outlier detection and calibration are very important. The subsequent steps of data fusion seem easier, as many groups already have data fusion software and experience.
- Suppose that for every hour in a test-period we take the locations of the sensors and create synthetic data based on the actual deviations of (co-located) raw sensor data in 2020 and 2021.
- We could use the synthetic data set to better check our outlier detection and calibration schemes.



- Investigate if it is worth the effort to try and use synthetic PM2.5 data to better evaluate the results of our outlier detection / calibration.
- If so, what criteria do we need for the synthetic PM2.5 data?
- If not, are there other (better?) ways to evaluate the results of our outlier detection / calibration?



- Benchmarking is an important step in reconciling and comparing results from different approaches of deploying low-cost sensor networks.
- Robust methodology using data from a large network (>1500 sensors).
- Variety of approaches and tools applied for calibration and data fusion using to the same dataset
 - Data fusion – network PM_{2.5} map with cleaned/calibrated data.
 - Benchmarking of sensors located closer to official monitors.
 - Inter- and intra- comparison of sensor groups.
 - Exploration of AI/ANN.
- Importance of data cleaning and fusion, handling of uncertainty, interpolation and calibration demonstrated and investigated.

- The quality of the **present generation** of low-cost PM2.5 sensors is such that results of **individual sensors** have limited use. When the information of **larger numbers of sensors** is combined, meaningful results may be obtained.
- CT6 is working on different approaches to process sensor data and extract the most useful data.

1. **Present status:** Work in progress on several different strategies for selection, calibration and data fusion of low-cost sensor data.
 - Further develop the different approaches.
 - Define a metric to evaluate sensor calibration.
 - Quantify and compare results obtained using different approaches
2. **Next steps:**
 - Identify and combine/integrate the strong points of the different approaches.
 - Optimal use of the calibrated sensor data in data fusion/data assimilation schemes.
 - Test synthetic data for evaluating different approaches.

<https://fairmode.jrc.ec.europa.eu/activity/ct6>

Next steps → Publications?

End of 2022: Status overview, best practices, benchmark results as a FAIRMODE/JRC document.

We presently aim for two scientific publications in 2022:

- Publication around the summer on the creation and use of synthetic data to test several data processing approaches.
- Publication around the end of 2022 on the overall experiences, guidance, best practices of processing data from low-cost sensor networks.

If possible, create a standard set of (synthetic) data for general use.



Benchmark on methodologies to integrate low-cost sensor networks with official measurements and modelled data; Status and first results

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Thank You !