Opportunities and challenges of air quality sensor networks. Experience in Norway.

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NILU Norsk institutt for luftforskning
Norwegian Institute for Air Research

Experience from past projects

CITI-SENSE

hackAIR

LEOPARD

Citi-Sense-MOB

InnoSense

IFLINK

NILU

2012

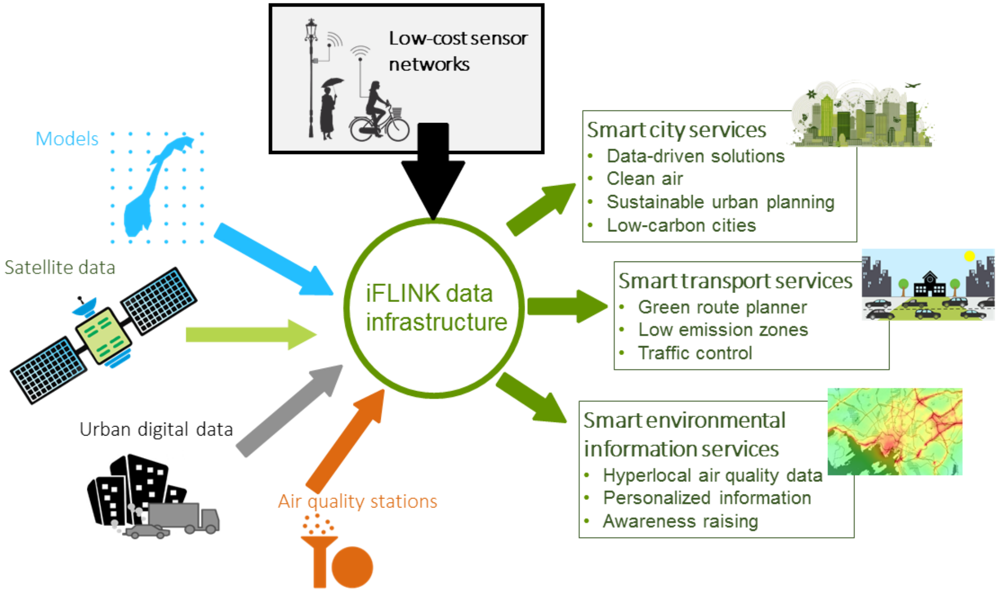
2019

http://iflink.nilu.no/

iFLINK

Innovative management of air quality and environment in Norwegian municipalities (2019-2021)

Motivation



iFLINK addresses three main research challenges:

- The **accuracy of environmental low-cost sensors**; i.e. how to ensure that sensor data quality is sufficient for the anticipated use of the data,
- The **design of a scalable open data infrastructure** that allows the connection of different types of sensors independent of the data format and location, and
- **Information solutions** aiming at engaging people, industries and communities in addressing complex environmental issues, such as air pollution, climate change and noise.

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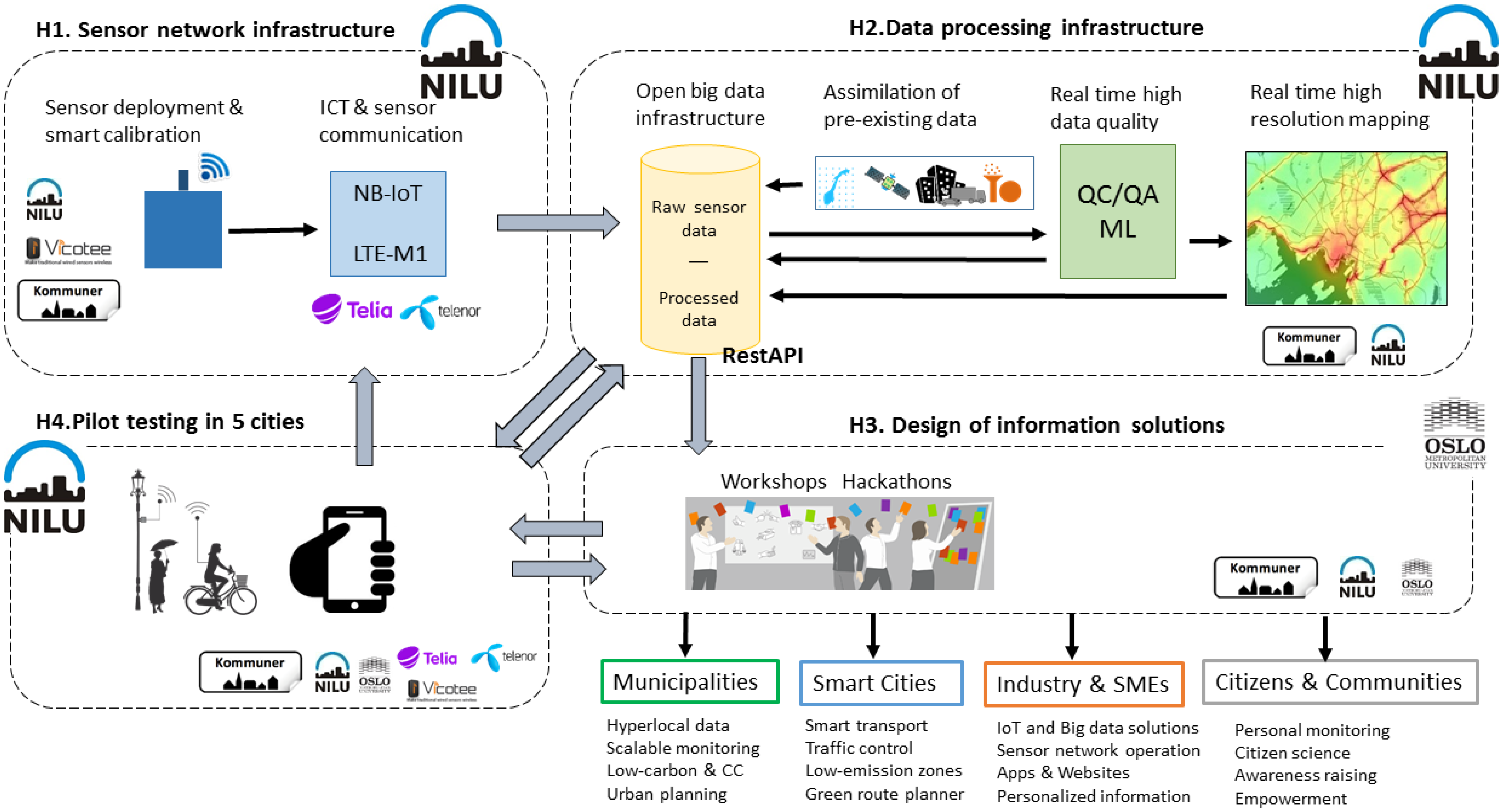
R&D activities



Selection of sensor systems

Vaisala Air Quality Transmitter AQT410

Overview | Technical Specifications | Documents

Overview

Vaisala Air Quality Transmitter AQT410 measures the most common gaseous pollutants nitrogen dioxide (NO2), sulphur dioxide (SO2), carbon monoxide (CO) and ozone (O3). The AQT410 measurement performance is based on proprietary advanced algorithms that enable ppb measurements at an affordable price using electrochemical sensors.

AQT410 has been specifically designed for air quality monitoring networks in urban areas, road networks or around industrial sites and airports. Thanks to its small weight and compact size it is ideally suited for deployment even in large air quality networks.

HOME ABOUT PRODUCT PERFORMANCE SUPPORT NEWS CONTACT

AQMesh

Search ... SEARCH

A revolution in air quality monitoring

3 JANUARY 2017 — PLUME LABS

Meet Flow, your smart mobile air quality tracker

For the past two years, Plume Labs has had one mission: helping you stay ahead of air pollution to improve your environmental health.

Today we are incredibly proud to **unveil the design of Flow by Plume Labs**, the first smart, mobile air quality tracker.

THE AIRCASTING PLATFORM

HOW IT WORKS

your air quality sensor

AIRBEAM

Information about performance is lacking.

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Spesifikasjoner for sensorsystemer til måling av luftkvalitet

Anbefalinger ved anskaffelse

Franck R. Dauge, Leif Marsteen, Philipp Schneider

Manufacturers should provide tests from independent laboratories!!

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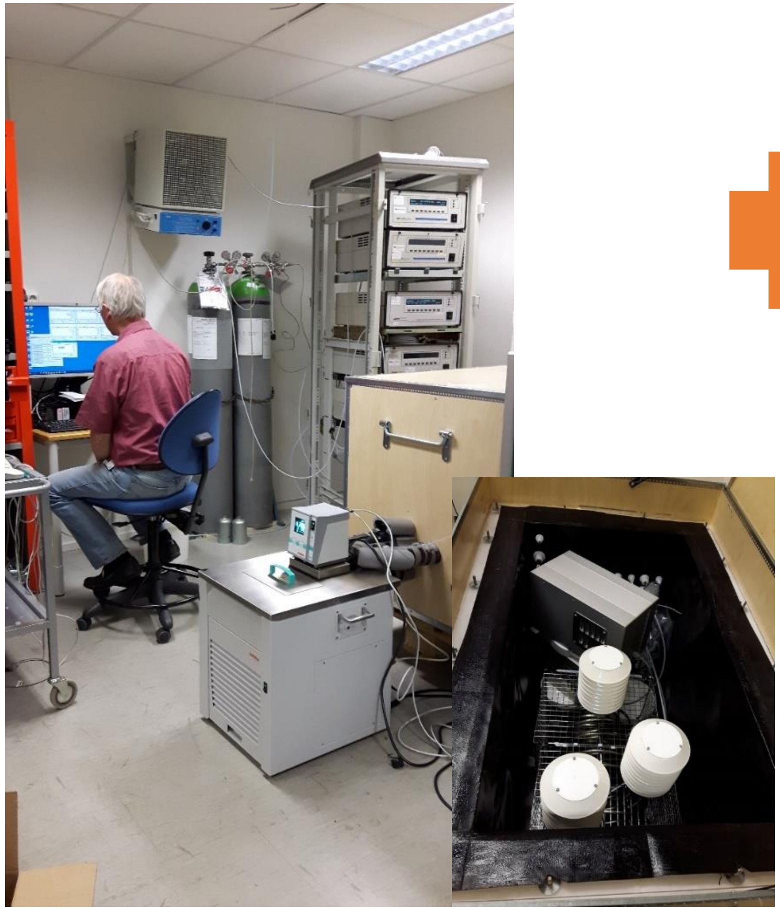
Evaluation of sensor system performance

Laboratory



Field co-location

- Using approved reference measuring methods
- Lab: Controlled conditions for temperature, humidity & gas concentrations
- Lab Analysis: pre-calibration, repeatability, LOD, temp/RH interference
- Field: Real-world conditions,
- Field Analysis: calibration, intercomparability, temp/RH interference
- Simultaneous evaluation of 3 units

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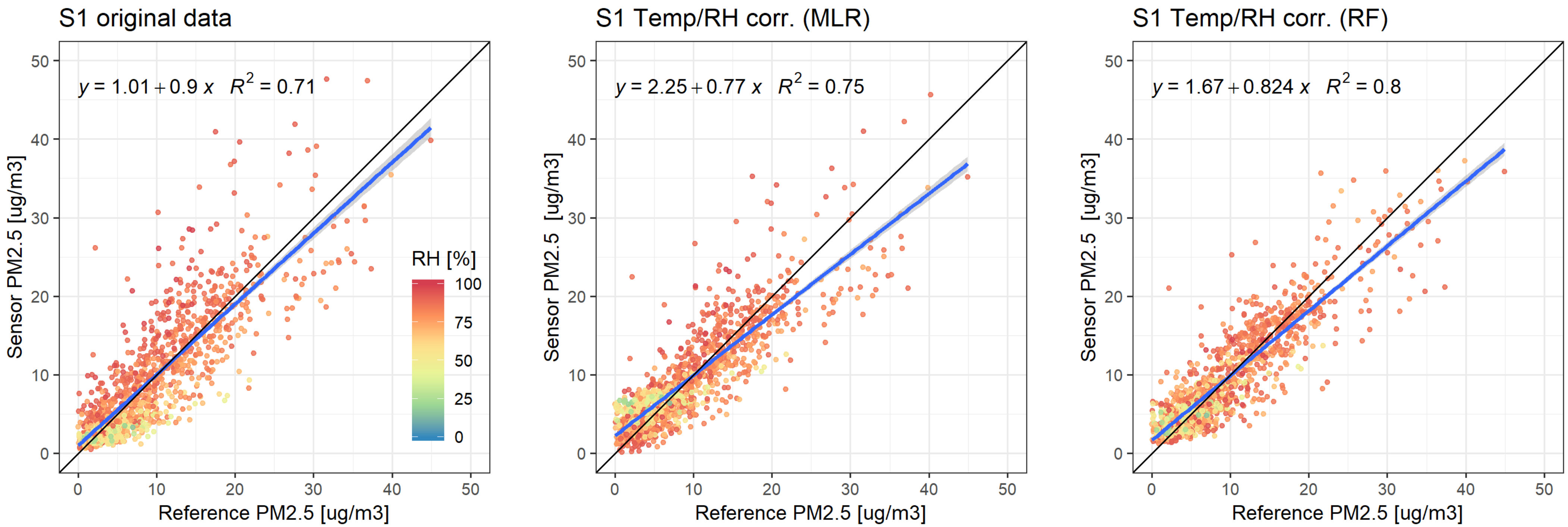
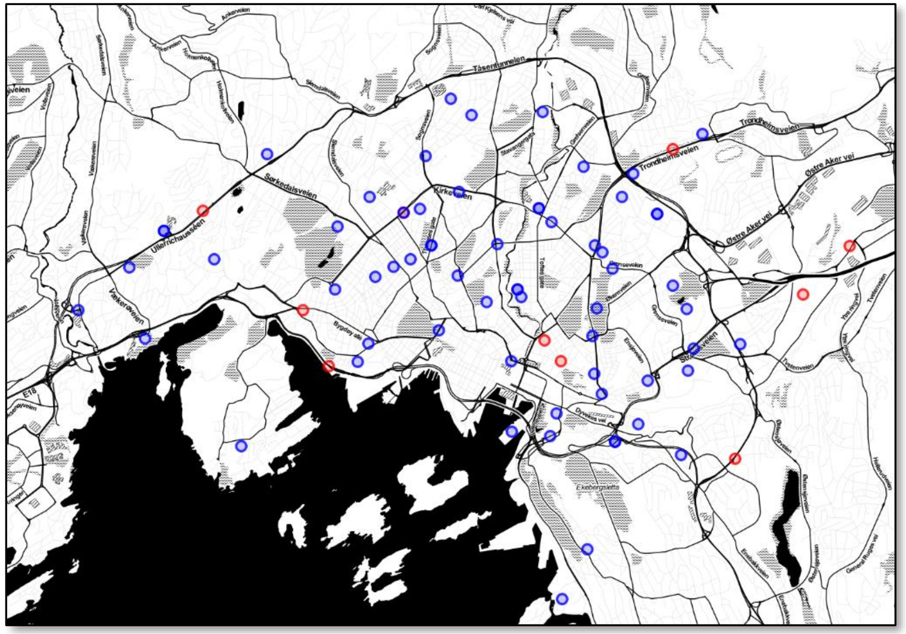
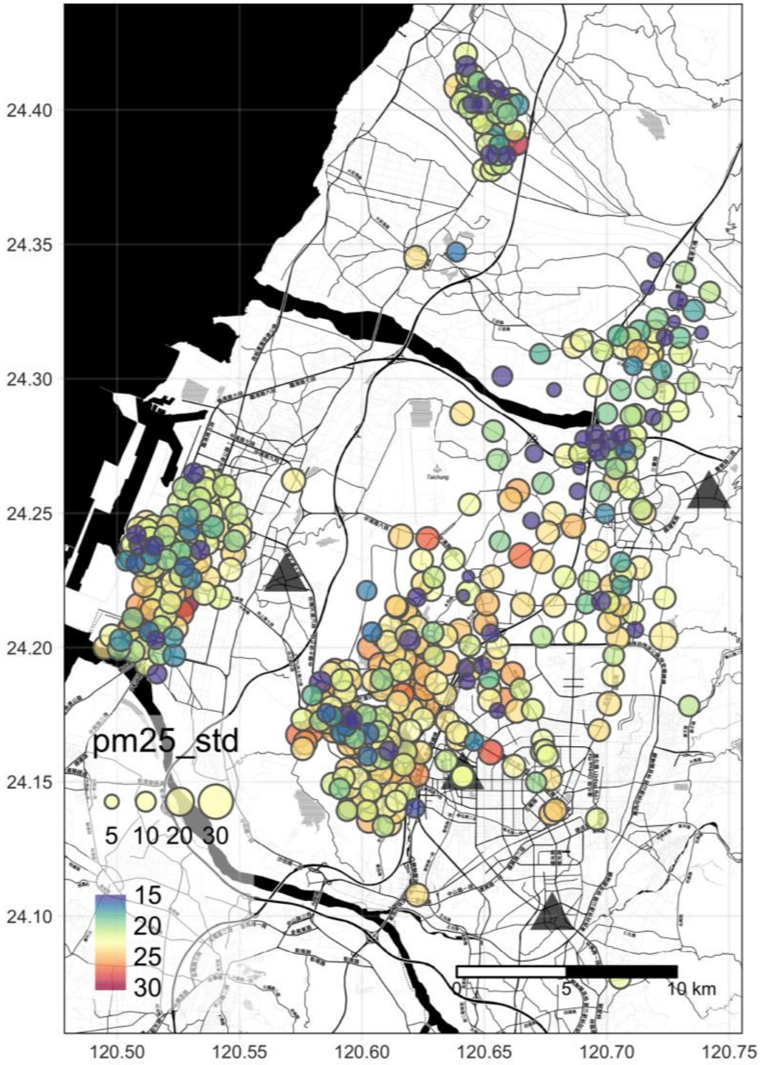
Calibration of sensor systems



Calibration against reference instrumentation improves sensor data quality, but, there are many open questions: how long does the co-location needs to be?, how often do we need to re-calibrate?
More research is needed in smart calibration techniques.

From sensor units to sensor networks





- The selection of locations will depend on the purpose of the network.
- Some often mentioned purposes are: hyperlocal monitoring and mapping
- Necessary automated solutions for managing dense sensor networks

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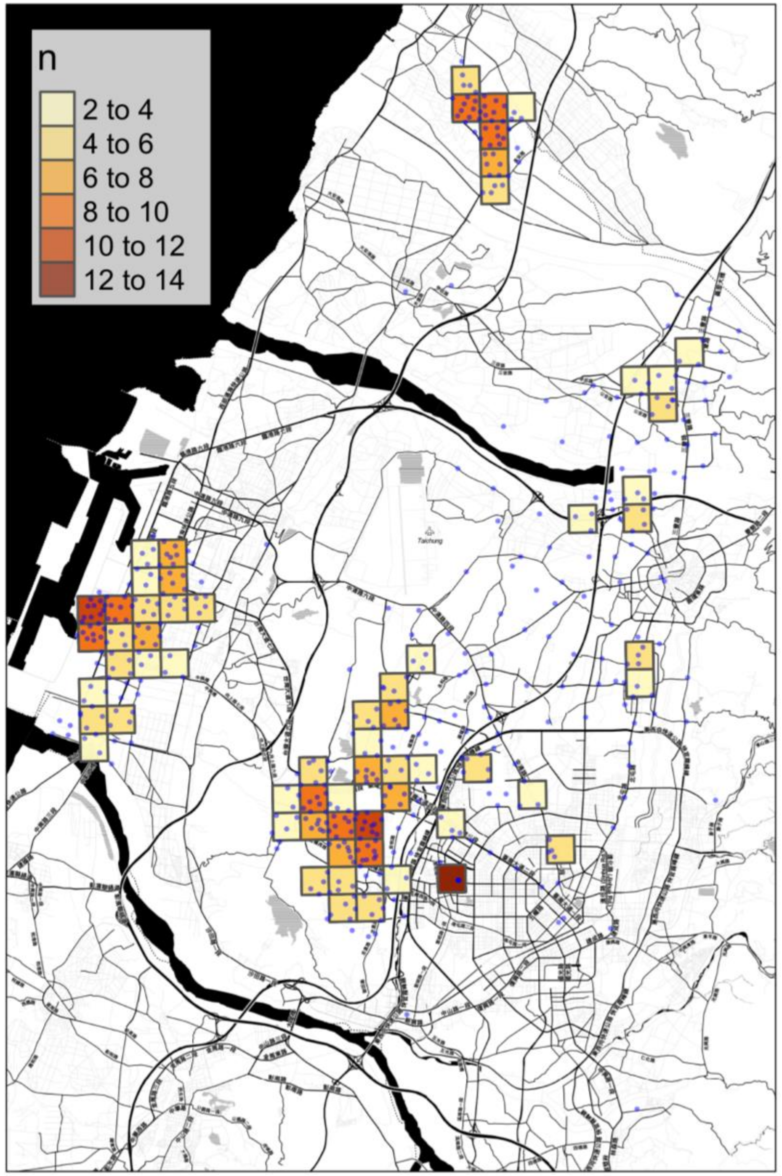
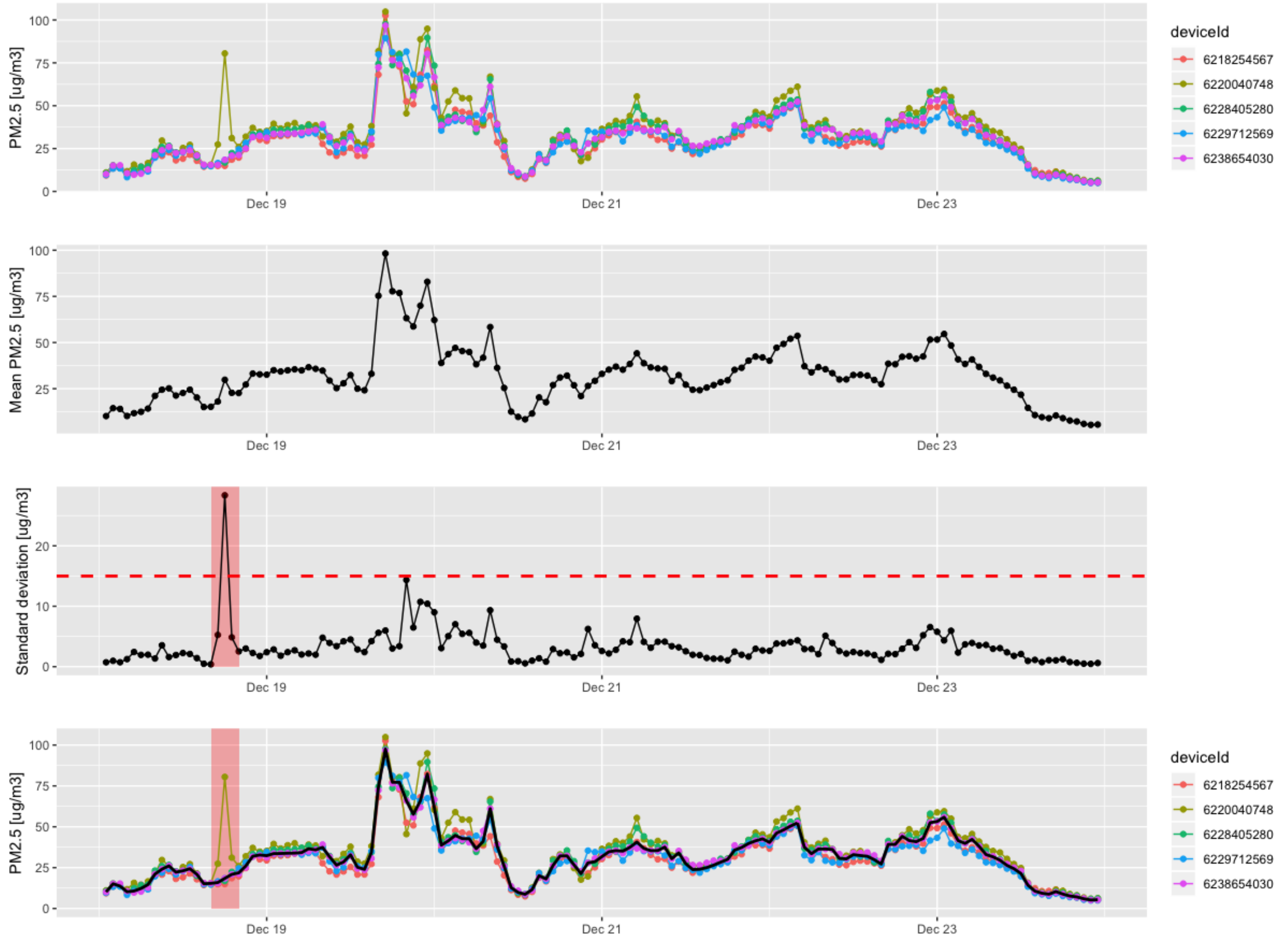
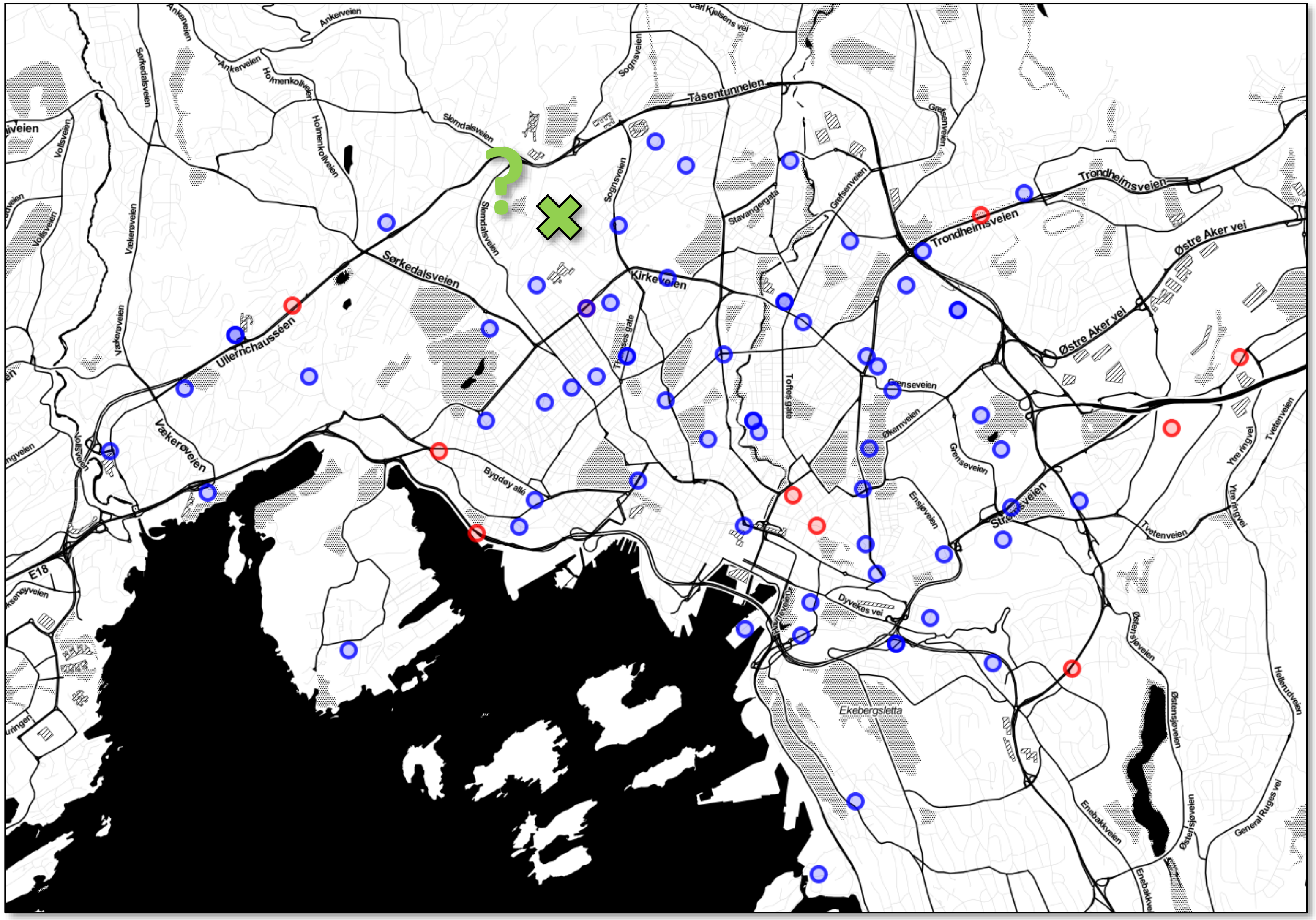
Automated QA/QC



In dense sensor networks, automated quality control (detection of drift, malfunctions, outliers) is crucial.



Use of sensor networks for air quality mapping



Red markers: Locations of Air Quality Monitoring stations for NO_2

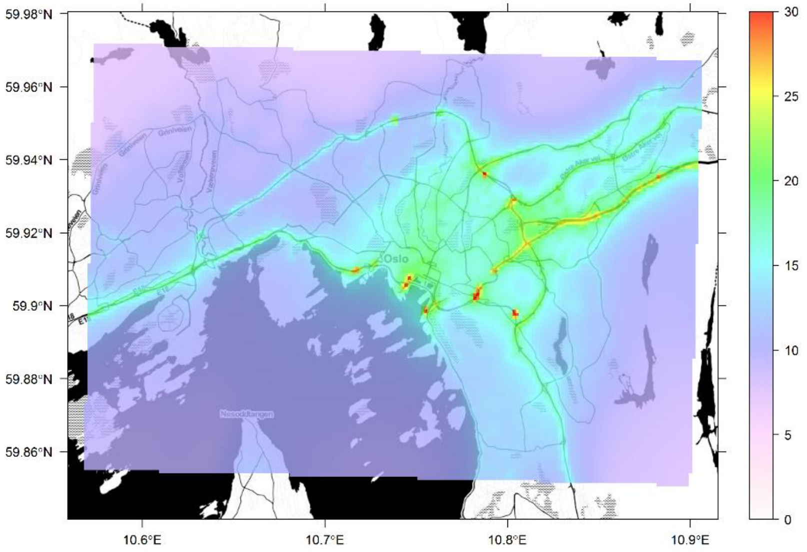
Blue markers: Deployment sites of low-cost sensors

An example of a previous sensor network deployed in the city of Oslo, Norway. 65 sensor nodes (mostly for NO2)

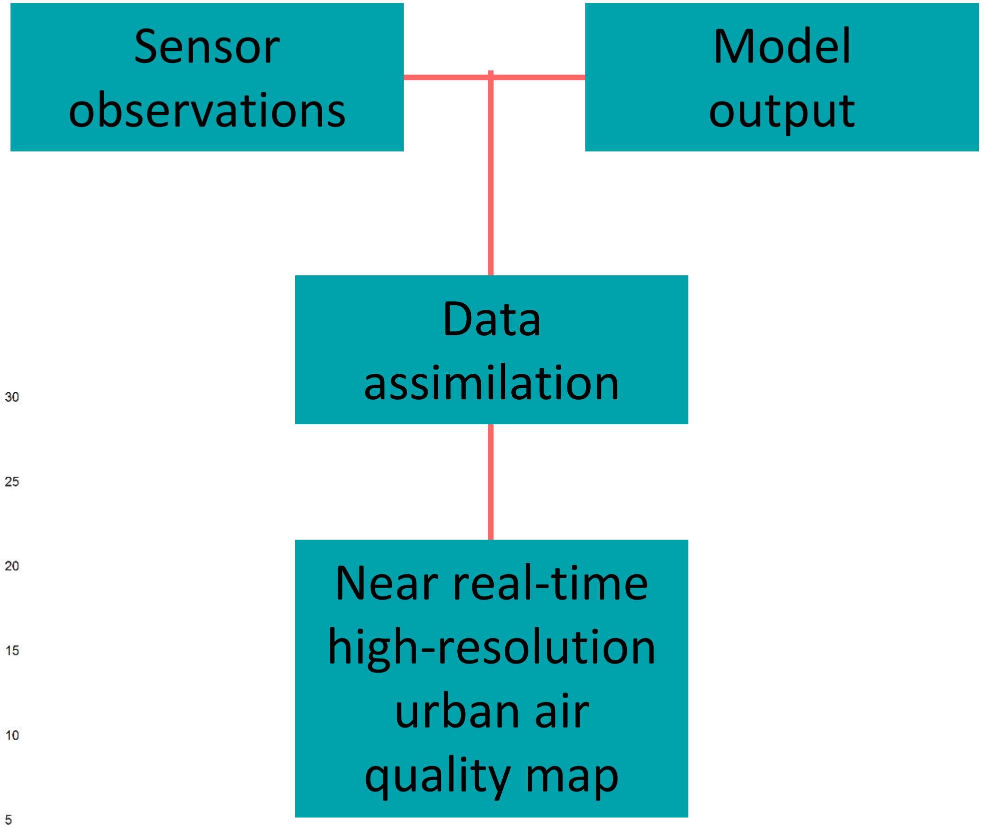
Combination with model output

Combining observations with model output through data fusion or data assimilation **adds value to both** input data sets:

- **Model is constrained** by actual observations
- **Observations are interpolated in space** in a physically meaningful way



Annual average concentration of NO_2 for Oslo as computed by the EPISODE urban air quality model.



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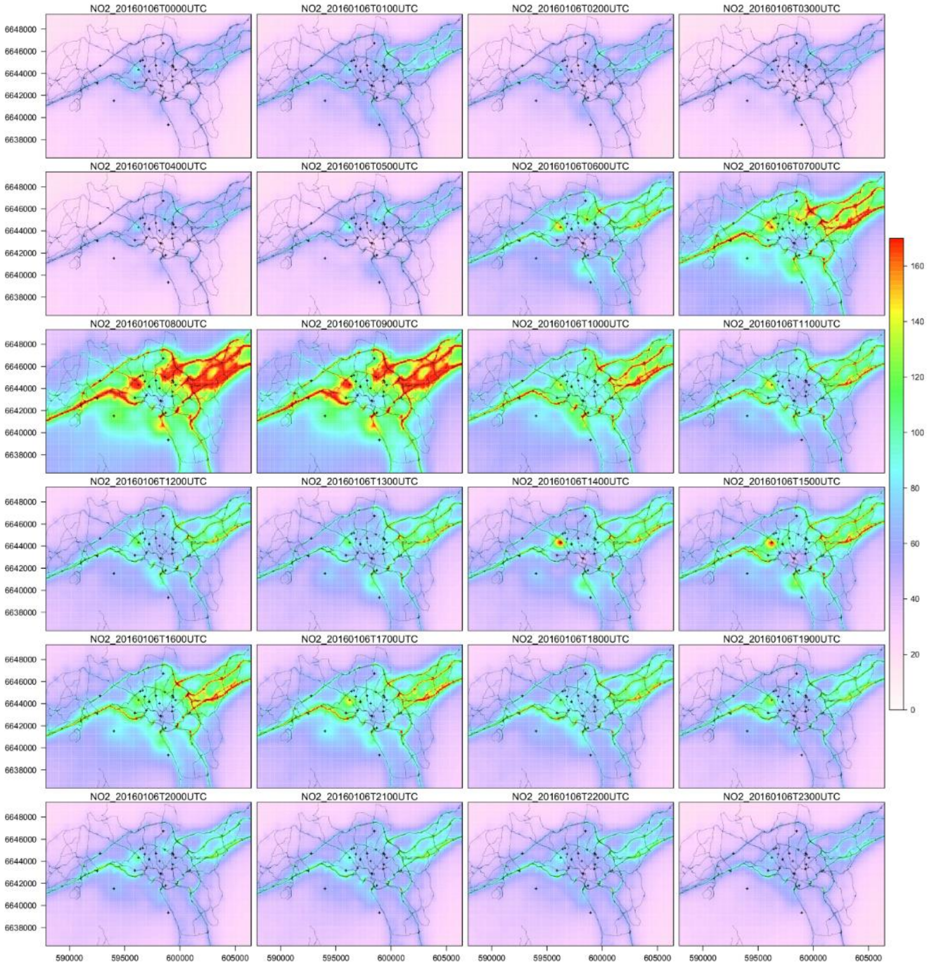
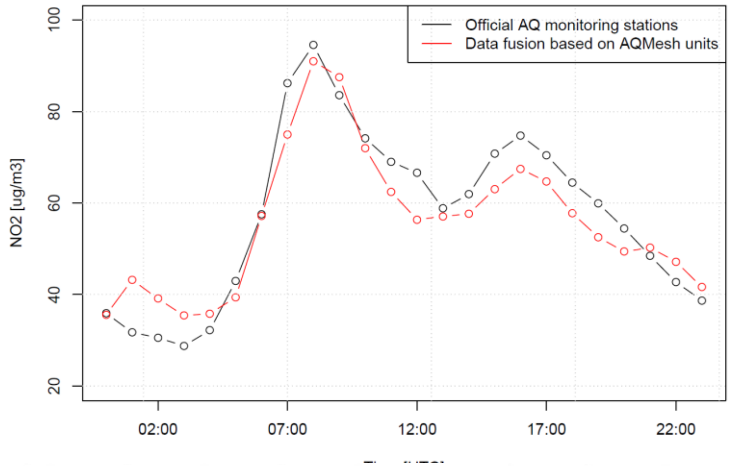
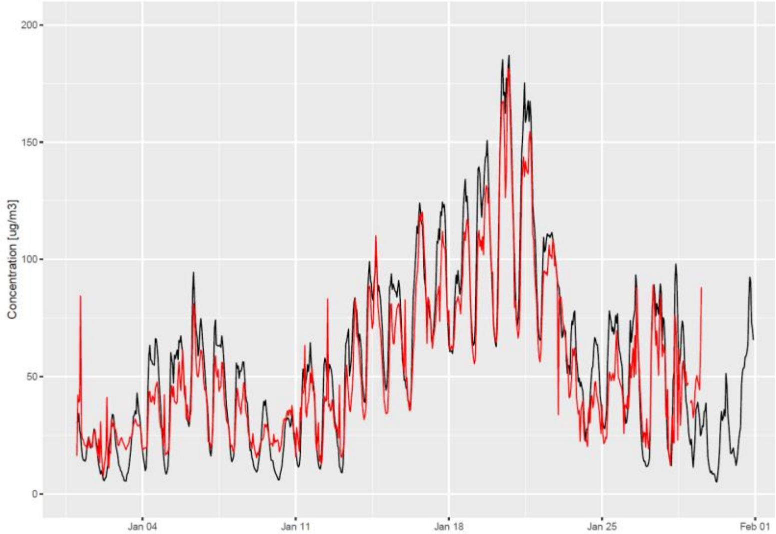
Previously: Geostatistical data fusion







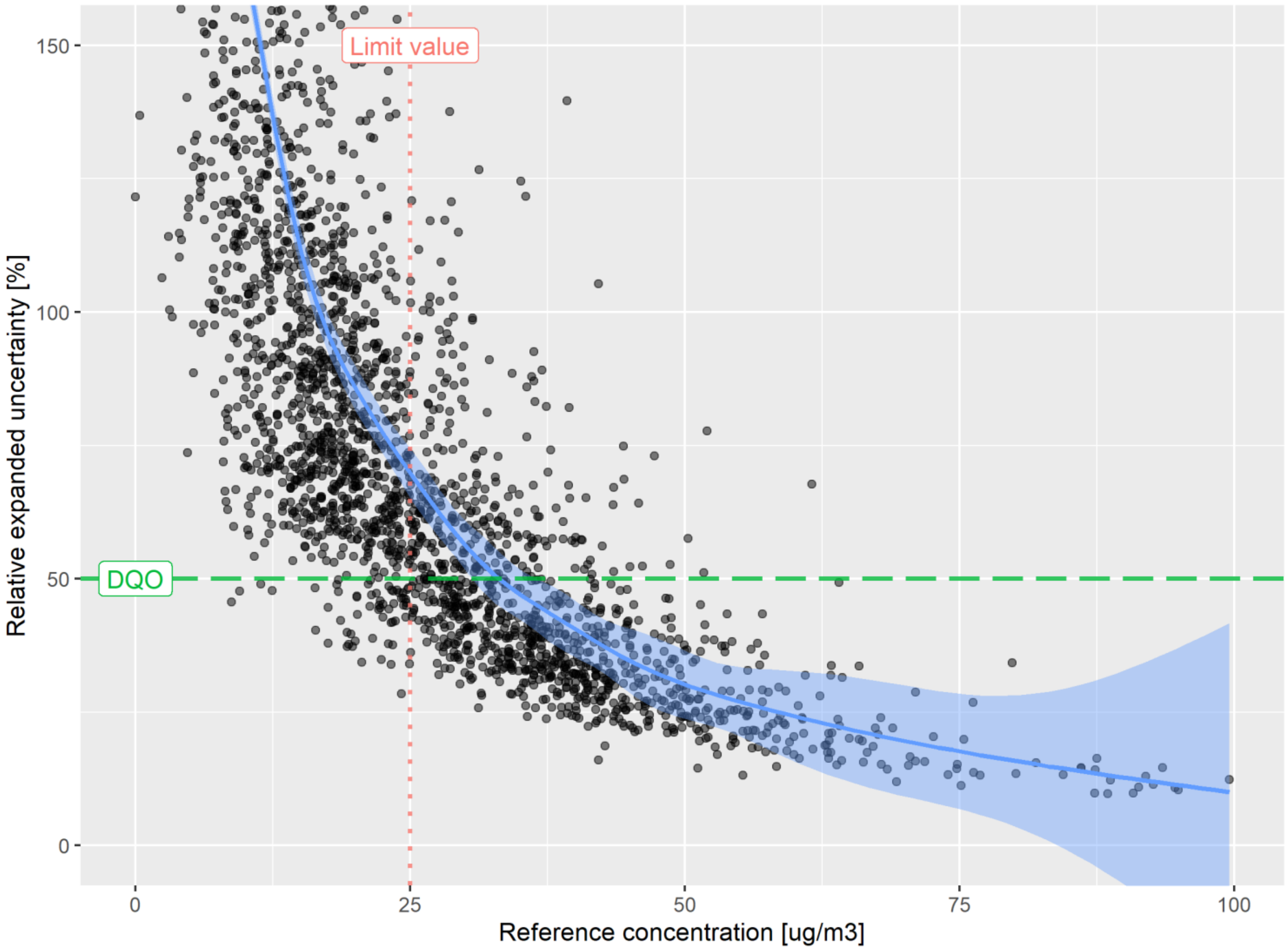
Schneider, P., Castell, N., Vogt, M., Dauge, F. R., Lahoz, W. A., & Bartonova, A. (2017). Mapping urban air quality in near real-time using observations from low-cost sensors and model information. *Environment international*, *106*, 234-247.

Schneider, P., Castell, N., Dauge, F. R., Vogt, M., Lahoz, W. A., & Bartonova, A. (2018). A Network of Low-Cost Air Quality Sensors and Its Use for Mapping Urban Air Quality. In *Mobile Information Systems Leveraging Volunteered Geographic Information for Earth Observation* (pp. 93-110). Springer, Cham.

Incorporating sensor uncertainty

In our previous data fusion method, sensor systems were assigned a constant weight.

Now we treat **each sensor system individually** and use a **temporally varying concentration-dependent uncertainty** for each time step



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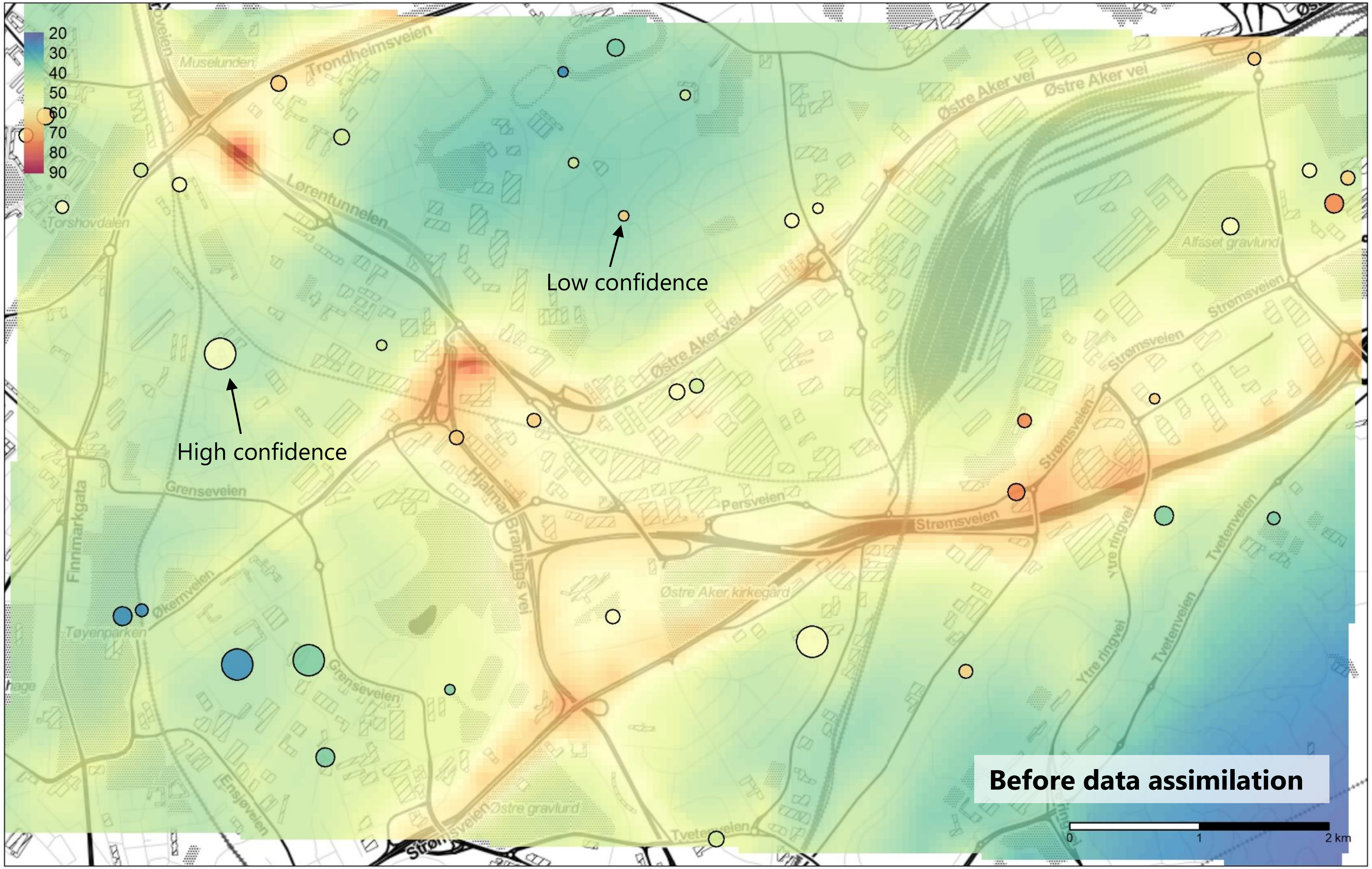

Urban-scale data assimilation of low-cost sensors in Norway

Model output at 25 m spatial resolution ("*a priori*") and hypothetical observations of NO_2 [in units of μg/m^3] from AQM stations and a low-cost sensor network of variable accuracy. The size of the marker indicates the accuracy of each observation (inverse of uncertainty).

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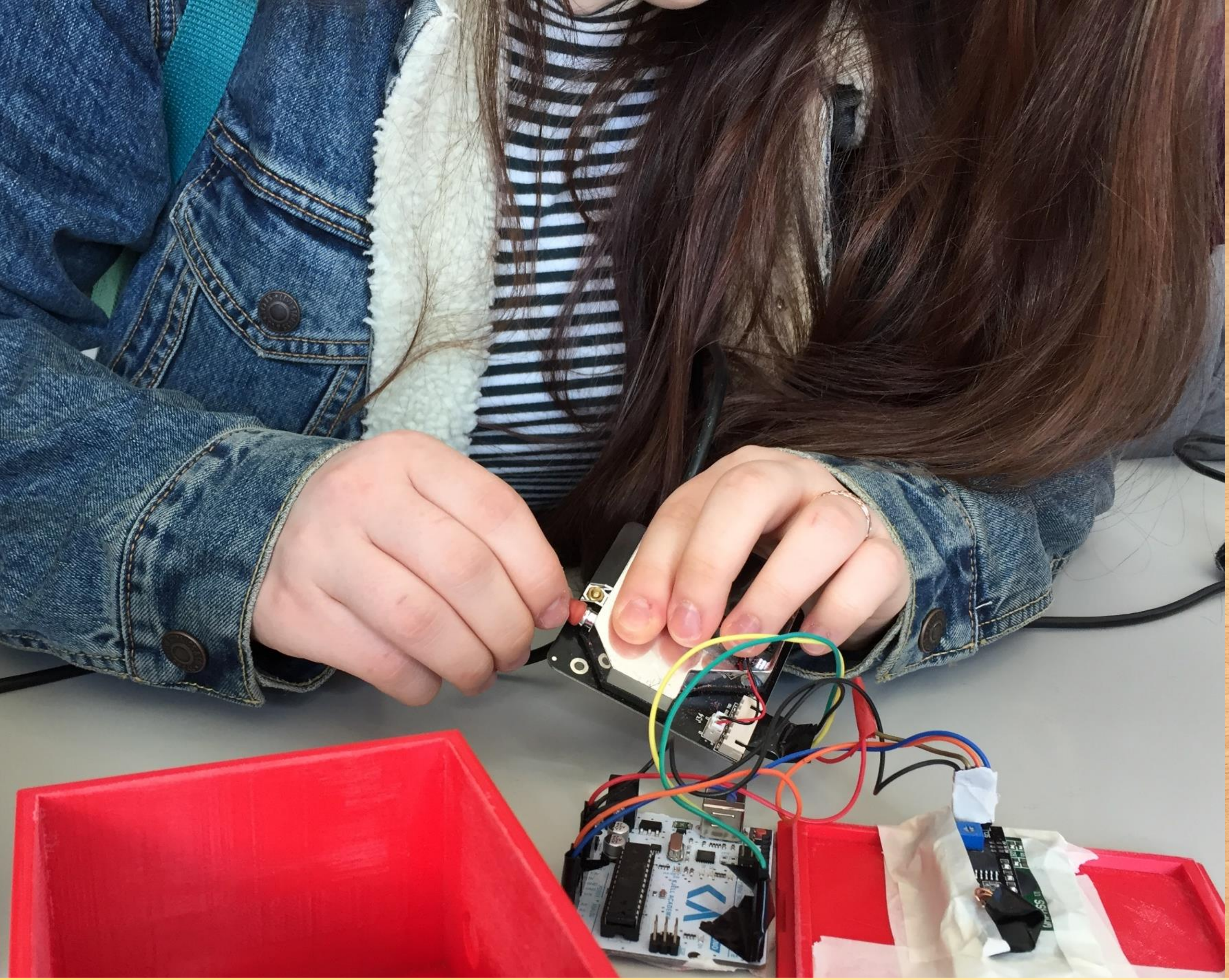
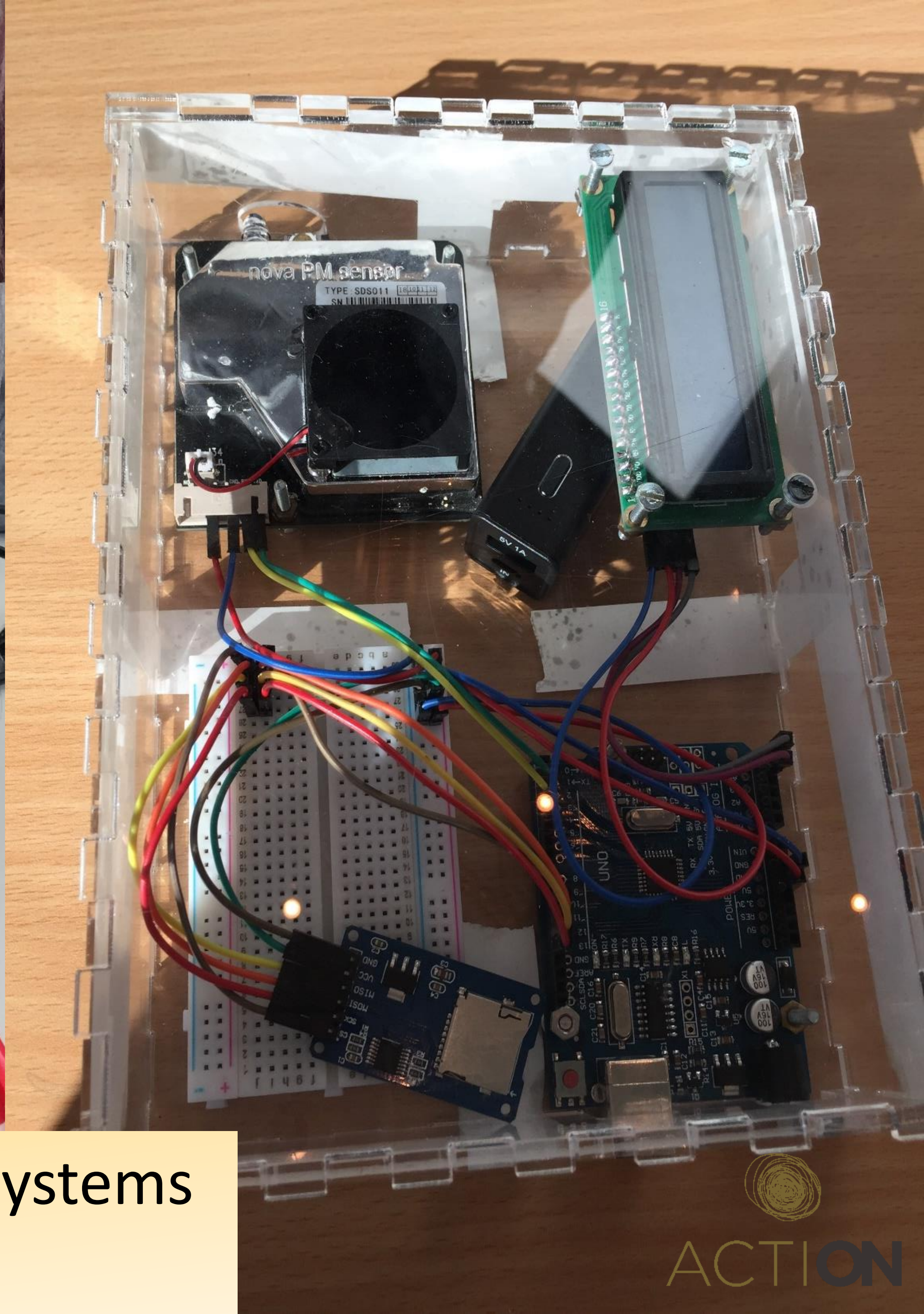
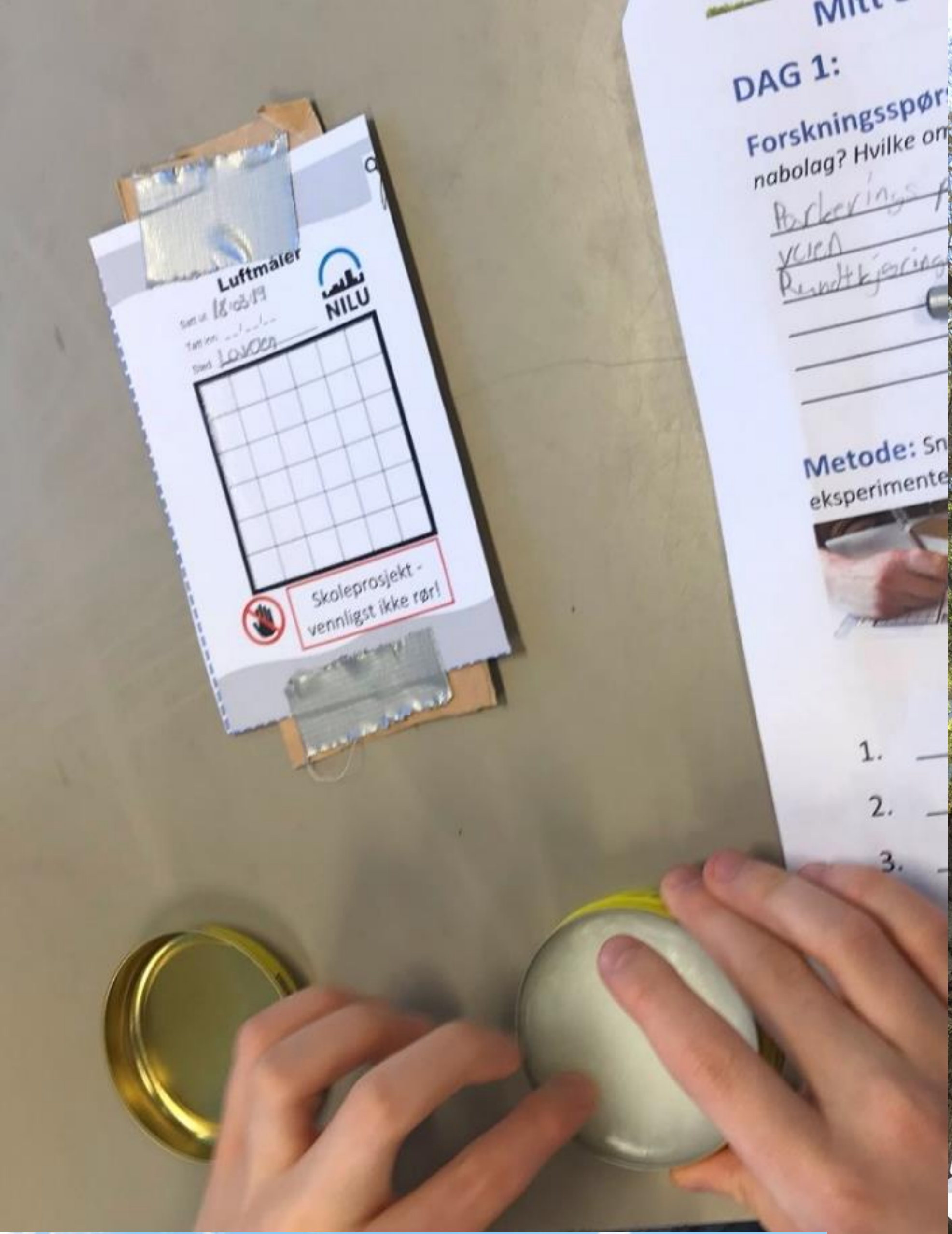




Citizen engagement in mounting low-cost sensor systems to monitor indoor and outdoor PM2.5.

ACTION



Engaging kindergarten and elementary schools in monitoring air quality using paper and Vaseline.

A short public service announcement…

New paper introducing standardized processing levels for low-cost sensors

Schneider, P., A. Bartonova, N. Castell, F. R. Dauge, M. Gerboles, G. S. W. Hagler, C. Hüglin, R. L. Jones, S. Khan, A. C. Lewis, B. Mijling, M. Müller, M. Penza, L. Spinelle, B. Stacey, M. Vogt, J. Wesseling, R. W. Williams (2019). ***Toward a Unified Terminology of Processing Levels for Low-Cost Air-Quality Sensors***. Environmental Science & Technology, 2019, 53, 15, 8485-8487.

Environmental Science & Technology

Viewpoint

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Toward a Unified Terminology of Processing Levels for Low-Cost Air-Quality Sensors

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Low-cost sensor systems for measuring air quality have received widespread scientific and media attention over recent years. It has become an established technical methodology to improve the data quality of such sensor systems by colocating them at traditional air quality monitoring stations equipped with reference instrumentation and field-calibrating individual units using various statistical techniques. Methods range from (multi)linear regression to more complex statistical techniques, often using additional predictor variables such as air temperature or relative humidity (e.g., Spinelle et al.[4]), and occasionally data not actually measured by the sensor system itself (e.g., station observations or model output). Most of these techniques improve the level of agreement between sensor-derived data and reference data, in many cases eliminating issues such as chemical interferences and sensor-to-sensor variability. It is not always clear, however, the extent to which the data arising from such processing are still a true and independent measurement by the sensor system, or some blend of secondary data and model prediction. Noticing this development, Hagler et al. (2018)[2] warned that some systems may use predictor variables for calibration in such a way that a line is crossed from justifiable and empirical correction of a known artifact to a method that is essentially a predictive statistical model. In addition, the processing steps that are carried out along the way are often not clearly communicated. The current lack of governmental or third-party standards for low-cost sensor performance[5] and occasional lack of distinction between sensors and sensor systems further complicates data processing.

Adding to the observations and recommendations made by Hagler et al. (2018)[2], we have further noticed that there is substantial and consistent confusion within both the scientific community and the interested public regarding the amount and type of processing applied to sensor data, and at what point derived data can be considered to have lost a meaningful link to quantitative traceability. The relevance of this issue to

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Level	Name	Definition	Example: Gas-sensors	Example: Particle-sensors
Level-0	Raw measurements	Original measurand produced by sensor system	Voltage corresponding to measured quantity, such as current for electrochemical and infrared sensors, resistance/ conductance for metal-oxide sensors	Voltage corresponding to current due to light scattered in nephelometers, or to binned counts for optical particle-counters
Level-1	Intermediate geophysical quantities	Estimate derived from corresponding Level-0 data, using basic physical principles or simple calibration equations, and no compensation schemes.	For electrochemical sensors, NO_2 concentration in µg/m^3 or ppb, using only Level-0 data from the NO_2 sensor itself with no additional corrections beyond factory calibration ("raw data in concentration units")	Binned particle-counts or PM mass in µg/m^3 derived from Level-0 data using simple calibration/assumed particle-density
Level-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)	NO_2 concentration in µg/m^3 or ppb, derived from onboard NO_2/NO/O_3 sensors, corrected for interferences and/or T/RH effects using onboard data	PM concentration in µg/m^3, corrected for T/RH effects with onboard-measured T/RH
Level-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)	As Level-2A but using external data from nearby station related to correcting for interferences based on the measurement principle (e.g. O3, T/RH)	As Level-2A but using external T/RH from nearby station
Measurement/prediction boundary				
Level-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)	NO_2 concentration in µg/m^3 or ppb, derived from Level-2A or Level-2B data, further corrected by proxies known to be correlated with NO_2, e.g. emissions or modeled NO_2	PM concentration in in µg/m^3 , derived from Level-2A or Level-2B data, further corrected by proxies known to be correlated with PM, e.g. emissions or modeled PM
Level-4	Spatially continuous geophysical quantities	Spatially continuous maps derived from network of sensor systems	Map of NO_2 concentrations in µg/m^3 or ppb, e.g. by assimilation of network data into a physical model	Map of $PM_{2.5}$ concentrations in µg/m^3, e.g. by assimilation of network data into a physical model

Schneider, P., A. Bartonova, N. Castell, F. R. Dauge, M. Gerboles, G. S. W. Hagler, C. Hüglin, R. L. Jones, S. Khan, A. C. Lewis, B. Mijling, M. Müller, M. Penza, L. Spinelle, B. Stacey, M. Vogt, J. Wesseling, R. W. Williams (2019). ***Toward a Unified Terminology of Processing Levels for Low-Cost Air-Quality Sensors***. Environmental Science & Technology, 2019, 53, 15, 8485-8487.

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Conclusions

- The **accuracy** of low-cost sensors is **improving**, increasing their potential for data assimilation
- In particular some **sensors for $PM_{2.5}$** consistently **reach R^2 values of 0.7** (hourly) **to 0.9** (24h) against reference-equivalent instruments
- **Assimilating data** from a dense sensor network into urban-scale models can add value to both datasets and **improve real-time urban-scale AQ mapping**
- The NILU urban AQ data assimilation system is model-independent, and sets particular emphasis on **integrating the uncertainty** for each individual sensor system
- It is possible to **involve citizens** and schools in monitoring air quality, increasing scientific knowledge and environmental awareness.
- Important to define a "common language" to describe data processing levels from sensor systems.

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