Quality control of $PM_{2.5}$ sensor networks and their use in mapping air quality

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6th EPCAC meeting, November 18-19, 2024

1. Quality controlling sensor data
2. Using sensors: Mapping with data assimilation
3. Using sensors: Mapping with Machine Learning

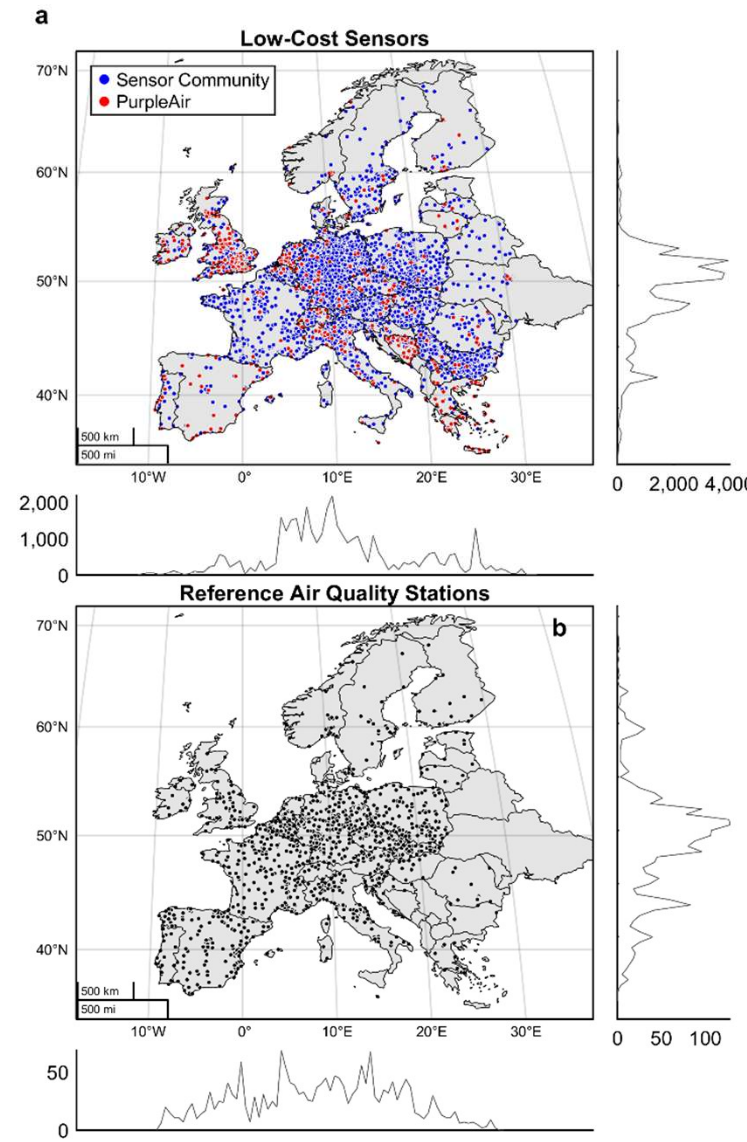
Quality controlling sensor data:
FILTER

Challenges with Adoption of Low-cost Sensor (LCS) Networks

- Data Quality
- Limited Interoperability Across Networks
- Lack of Standardized Semantic and Quality Control Frameworks
- Sensor-Specific Solutions Limit Scalability

→ **Need for an algorithm to automatically quality-control observations from large low-cost sensor networks**:

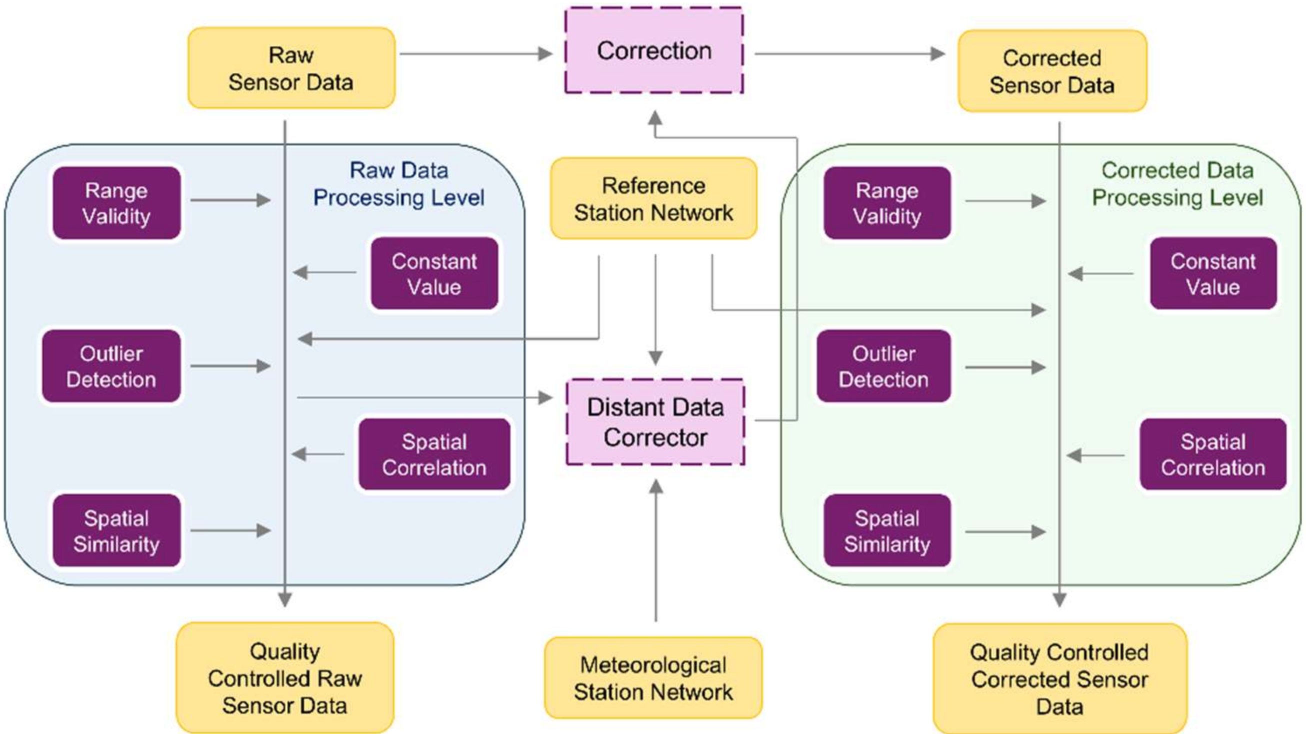
Hassani, A., Salamalikis, V., Schneider, P., Stebel, K., and Castell, N.: A scalable framework for harmonizing, standardization, and correcting crowd-sourced low-cost sensor PM2.5 data across Europe, Journal of Environmental Management, 380, 125100, https://doi.org/10.1016/j.jenvman.2025.125100, 2025.



FILTER: A framework to unify and flag sensor-based outdoor/static $PM_{2.5}$ data

Includes **two Processing levels** (“raw” and “corrected”) with five Quality Controls steps within each level

Output: Provides flags for all tests and labels data as “high quality”, “good quality”, or “other quality”, providing guidance to the user



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Quality Control	Plausible Values	Interpretation of Flags
Range Validity	Integer ∈ {0,1}	0: Out of range 1: Within the range
Constant Value	Integer ∈ {0,1,2}	0: Number of measurements in the window < 6 hours 1: Range ≤ 0.1 and number of measurements in the window ≥ 6 2: Range > 0.1 and number of measurements in the window ≥ 6
Outlier Detection	Integer ∈ {0,1,2,3}	0: Number of measurements in the window < 90 hours 1: Outlier, solely based on the sensor of interest data Not enough neighbors (either station or sensor) are found in the vicinity, meaning at least one within a radius of 3 km or at least 2 up to 30 km 2: Outlier, considering the neighbors 3: Not an outlier
Spatial Correlation	Integer ∈ {0,1,2,3}	0: The sensor of interest's data coverage in the window is < 90 hours 1: Not enough neighbors (either station or sensor) are found in the vicinity, meaning at least 1 with ≥ 90 hours paired measurements in the window up to 3 km or at least 2 with ≥ 90 hours paired measurements in the window up to 30 km 2: Correlation test with nearest neighbors is not satisfied. The sensor might be faulty or inaccurate, but the lack of correlation might be due to spatial variability 3: Correlated with neighbors Not having enough neighbors takes priority over lack of data coverage
Spatial Similarity	Integer ∈ {0,1,2,3}	0: The sensor of interest's data coverage in the window is < 90 hours 1: Not enough stations are found in the vicinity, meaning at least 1 with ≥ 90 hours paired measurements in the window up to 30 km 2: Spatial similarity test with nearest references is not satisfied. The sensor might be faulty or inaccurate, but the lack of similarity might be due to spatial variability 3: Spatially similar to nearest references

Hassani, A., Salamalikis, V., Schneider, P., Stebel, K., and Castell, N.: A scalable framework for harmonizing, standardization, and correcting crowd-sourced low-cost sensor PM2.5 data across Europe, Journal of Environmental Management, 380, 125100, https://doi.org/10.1016/j.jenvman.2025.125100, 2025.

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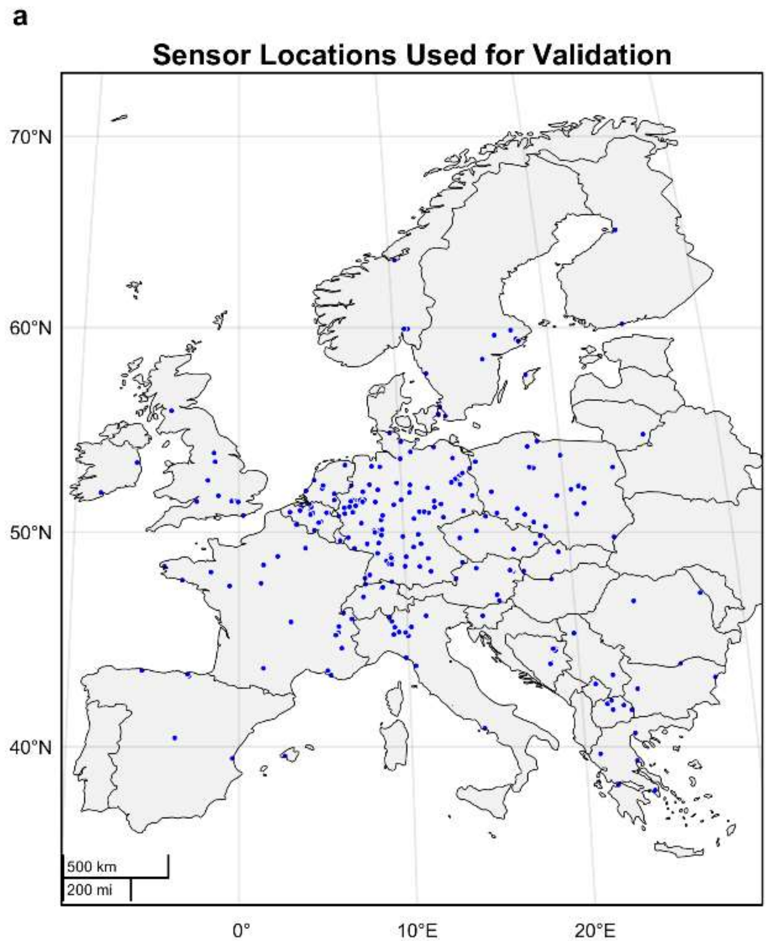
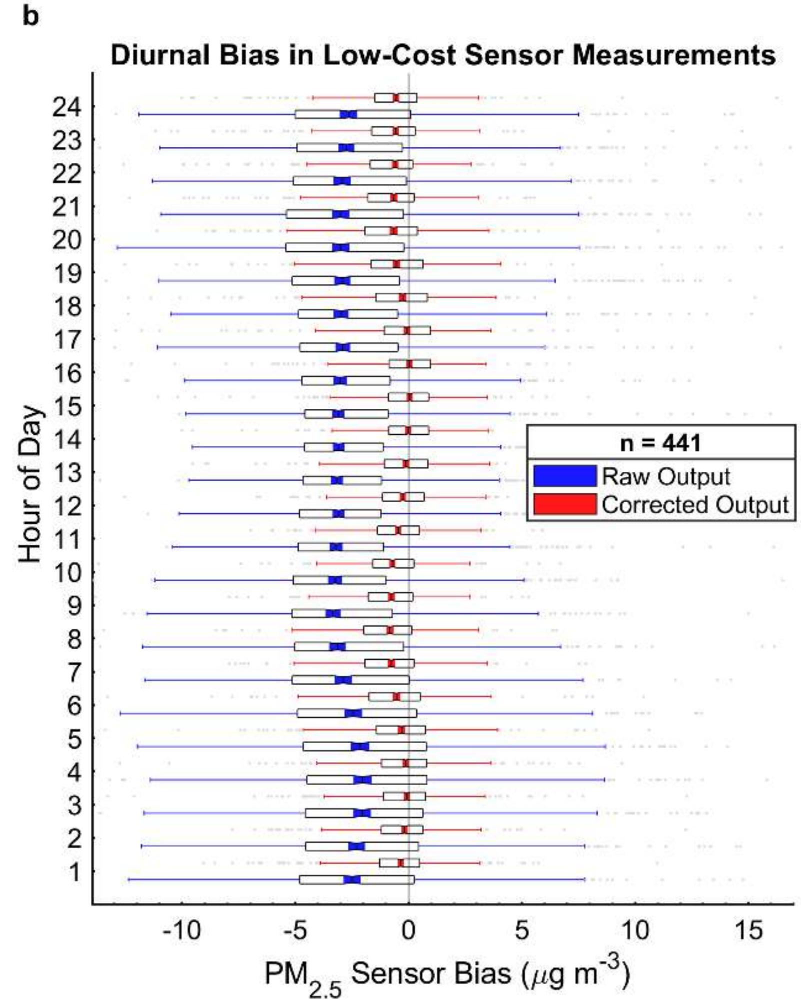
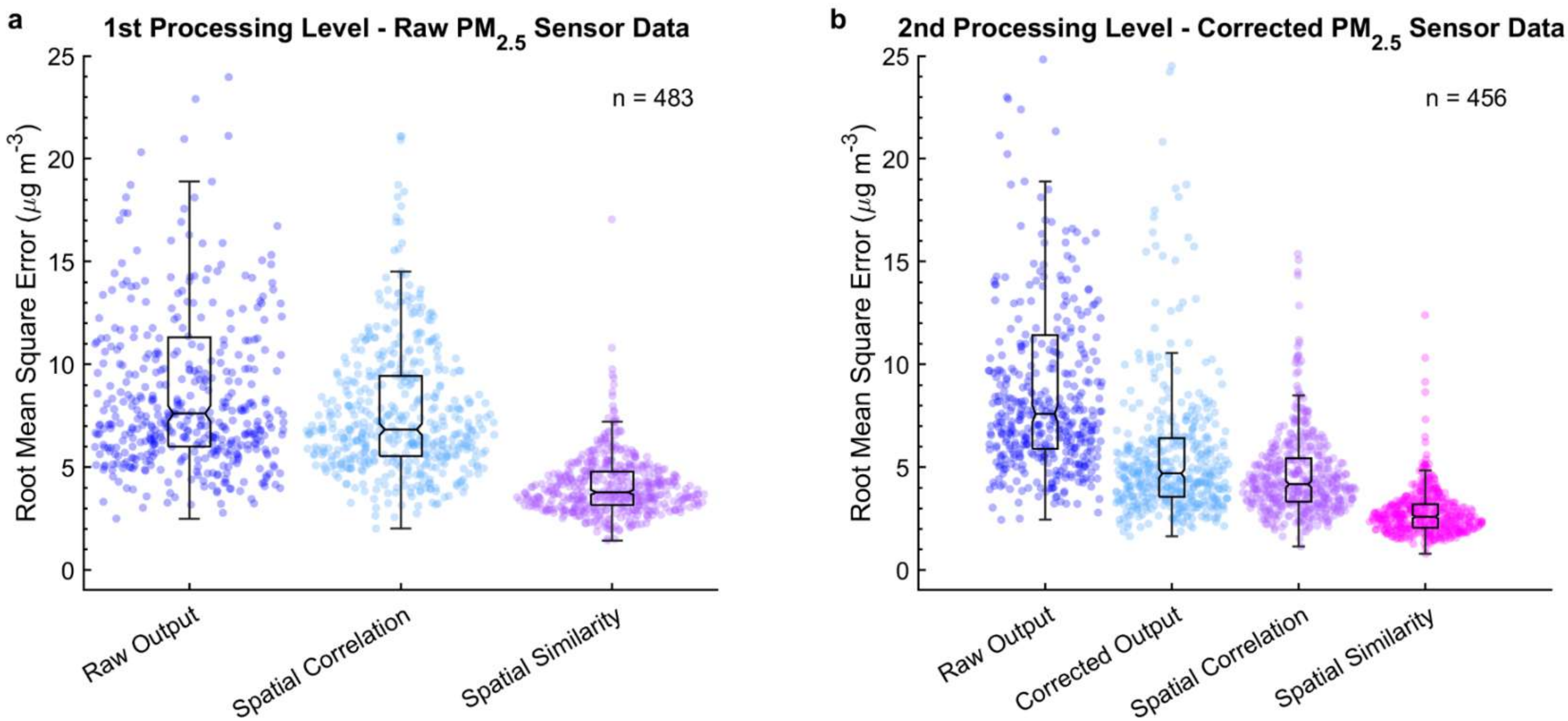
FILTER’s Effectiveness and Validation







Median bias across all hours of the day was **reduced by nearly 86 %**.

Median RMSE at both raw and corrected data processing levels **reduced around 50.3 % and 49.5 %**, respectively.

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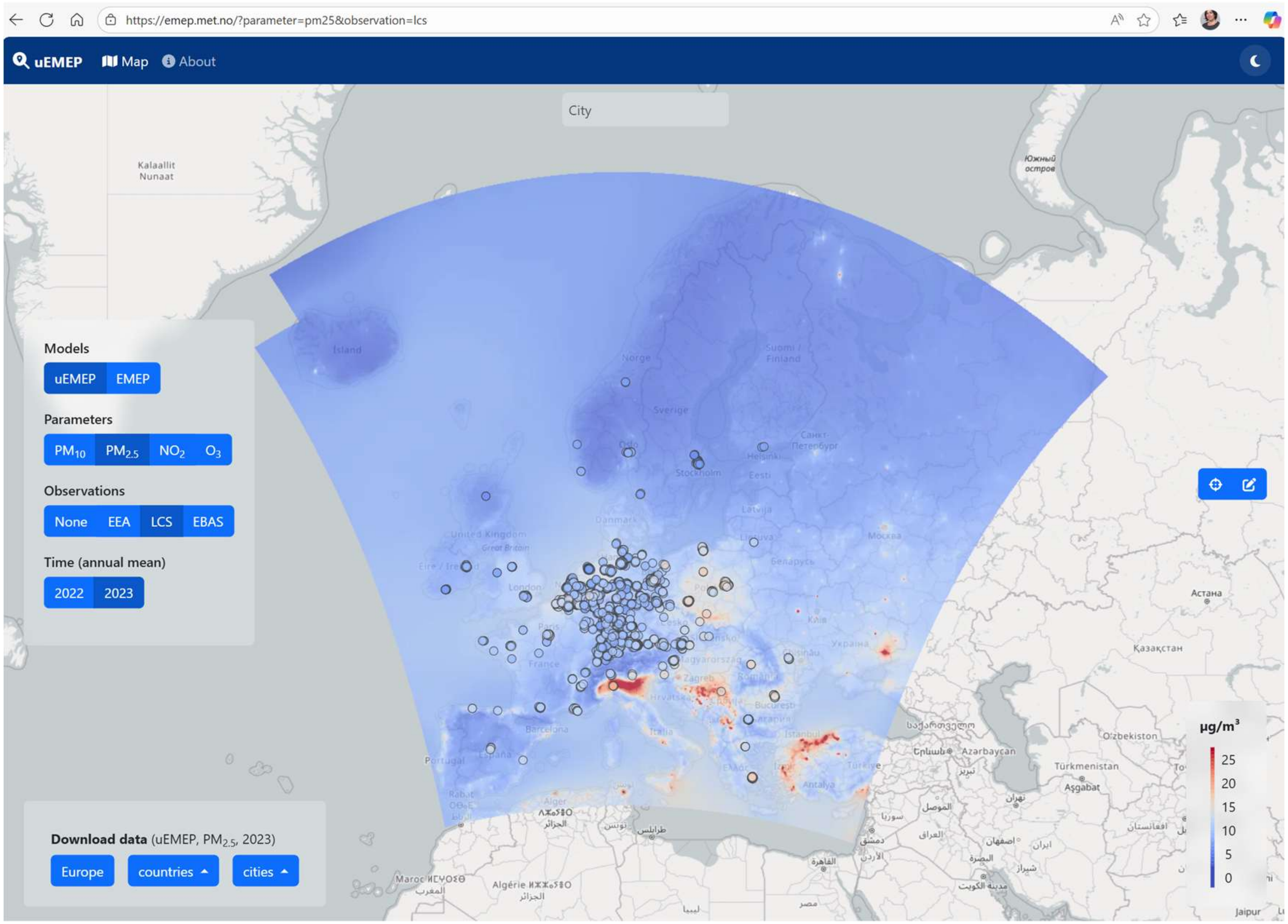

Sensor data used for EMEP & uEMEP model validation

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Mapping local-scale air quality:
Data assimilation

Goal: Combine $PM_{2.5}$ sensor data with high-resolution model output (e.g. EPISODE or uEMEP)

Approach: Offline analysis via Optimal Interpolation. Traditional data assimilation approach. Conceptually similar to geostatistics but more flexible in specifying the background error covariance.

Outcome: Corrected concentration field that combines model and sensors information by taking their respective uncertainty into account

Analysis field

$$\overset{\text{Analysis}}{\boxed{\mathbf{x}_a}} = \underset{\text{Background}}{\boxed{\mathbf{x}_b}} + \overset{\text{Weights}}{\boxed{\mathbf{W}}}[\underset{\text{Obser-vations}}{\boxed{\mathbf{y}_0}} - \overset{\text{Observation operator}}{\boxed{H}}(\mathbf{x}_b)]$$

Weights

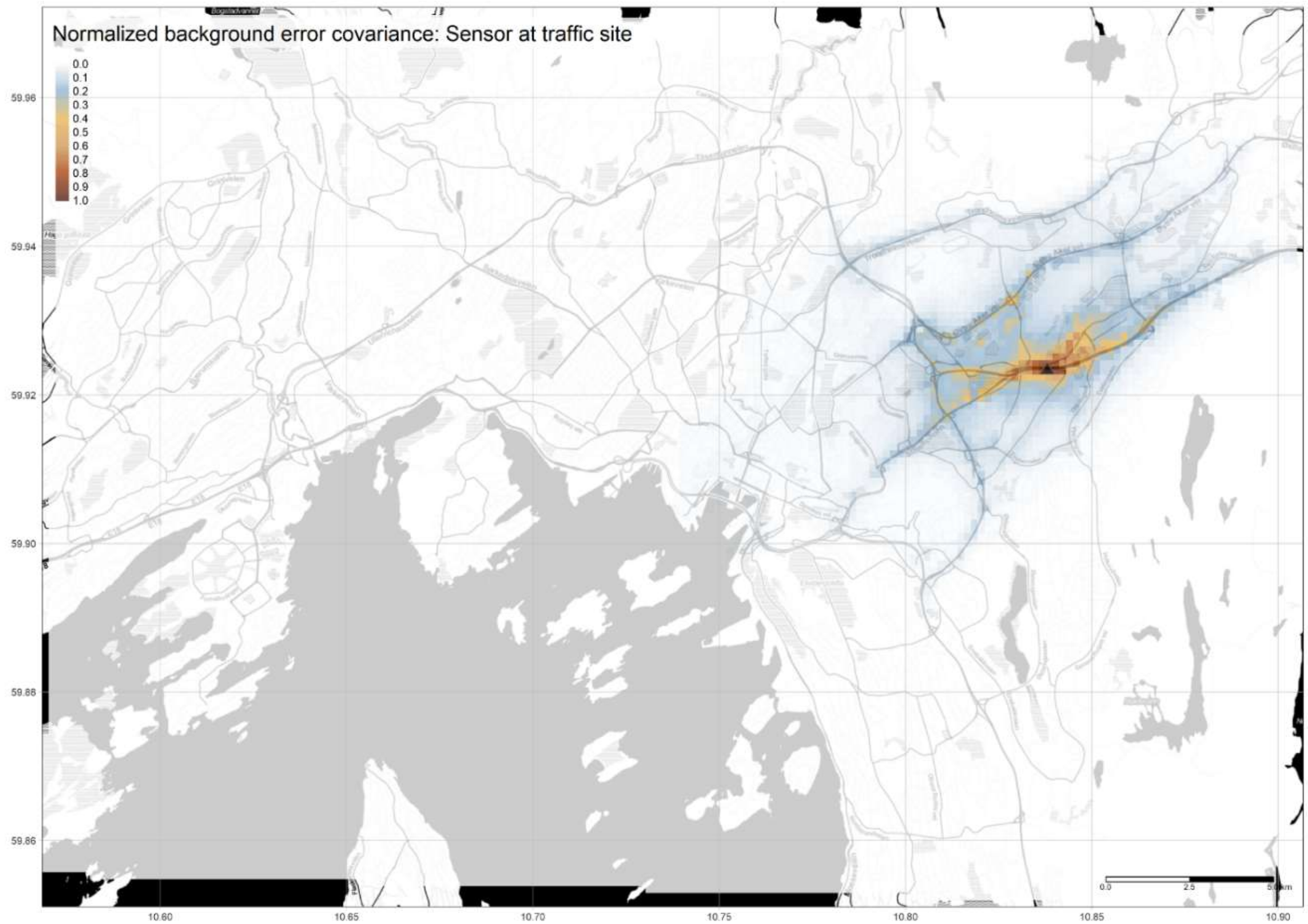
$$\mathbf{W} = \mathbf{B}\overset{\text{LTP of Obs. Op.}}{\boxed{\mathbf{H}}}^{\mathrm{T}}\left(\underset{\text{Observation error covariance}}{\boxed{\mathbf{R}}} + \mathbf{H}\overset{\text{Background error covariance}}{\boxed{\mathbf{B}}}\mathbf{H}^{\mathrm{T}}\right)^{-1}$$

Analysis error covariance

$$\overset{\text{Analysis error}}{\boxed{\mathbf{P}_a}} = (\underset{\text{Identity matrix}}{\boxed{\mathbf{I}}} - \mathbf{W}\mathbf{H})\mathbf{B}$$

Spreading information in space

- Overall model/background error covariance can be derived from comparison with stations
- However, spatial patterns in background error covariance are crucial and are more challenging to get right
- We use a combination of distance decay and spatial autocorrelation



A background error covariance matrix for a single sensor location in Oslo based on the EPISODE model (Hamer et al. 2020)

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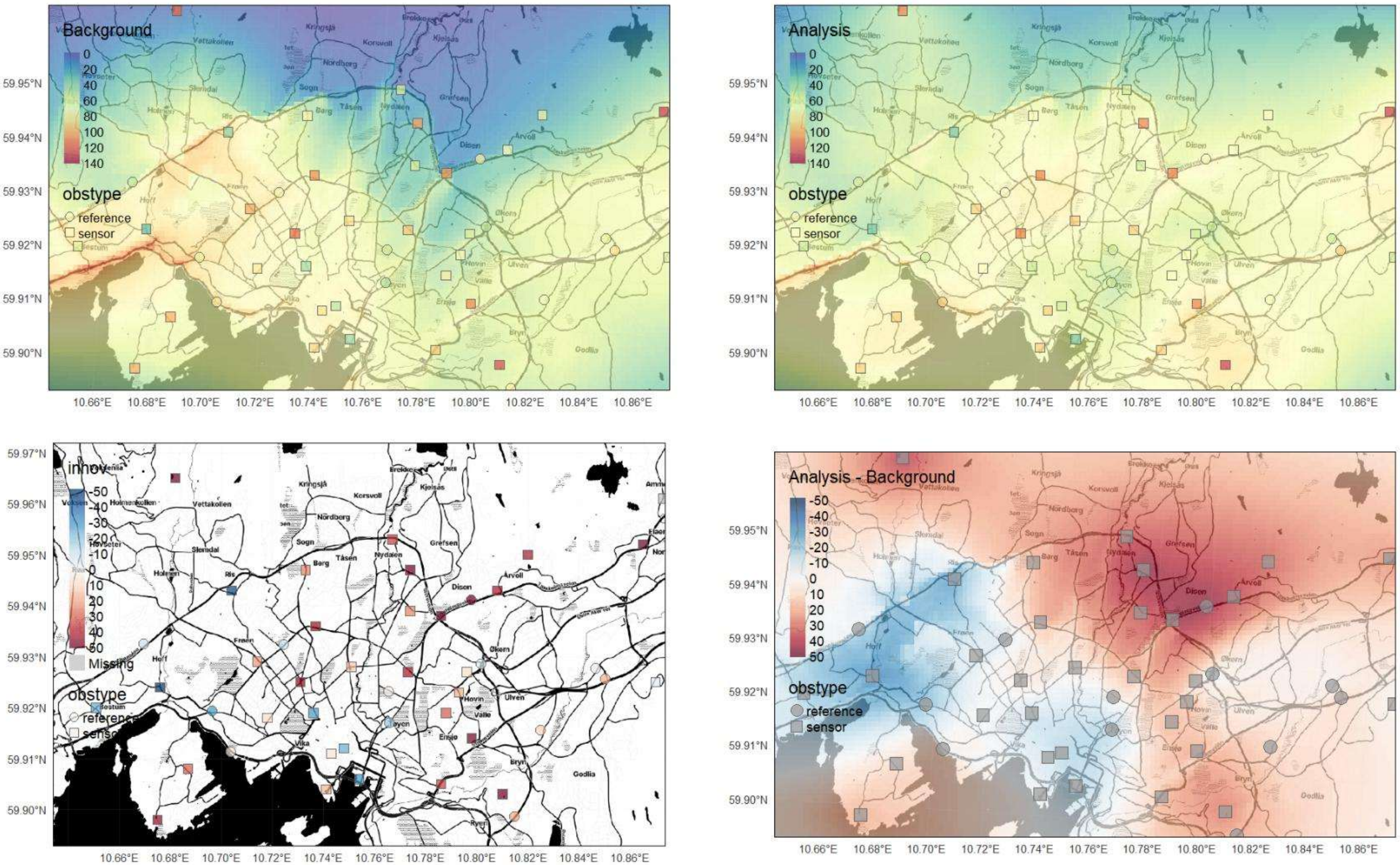
Background
0
20
40
60
80
100
120
140
obstype
reference
sensor
Analysis
innov
-50
-40
-30
-20
-10
0
10
20
30
40
50
Missing
Analysis - Background
59.95°N
59.94°N
59.93°N
59.92°N
59.91°N
59.90°N
10.66°E
10.68°E
10.70°E
10.72°E
10.74°E
10.76°E
10.78°E
10.80°E
10.82°E
10.84°E
10.86°E

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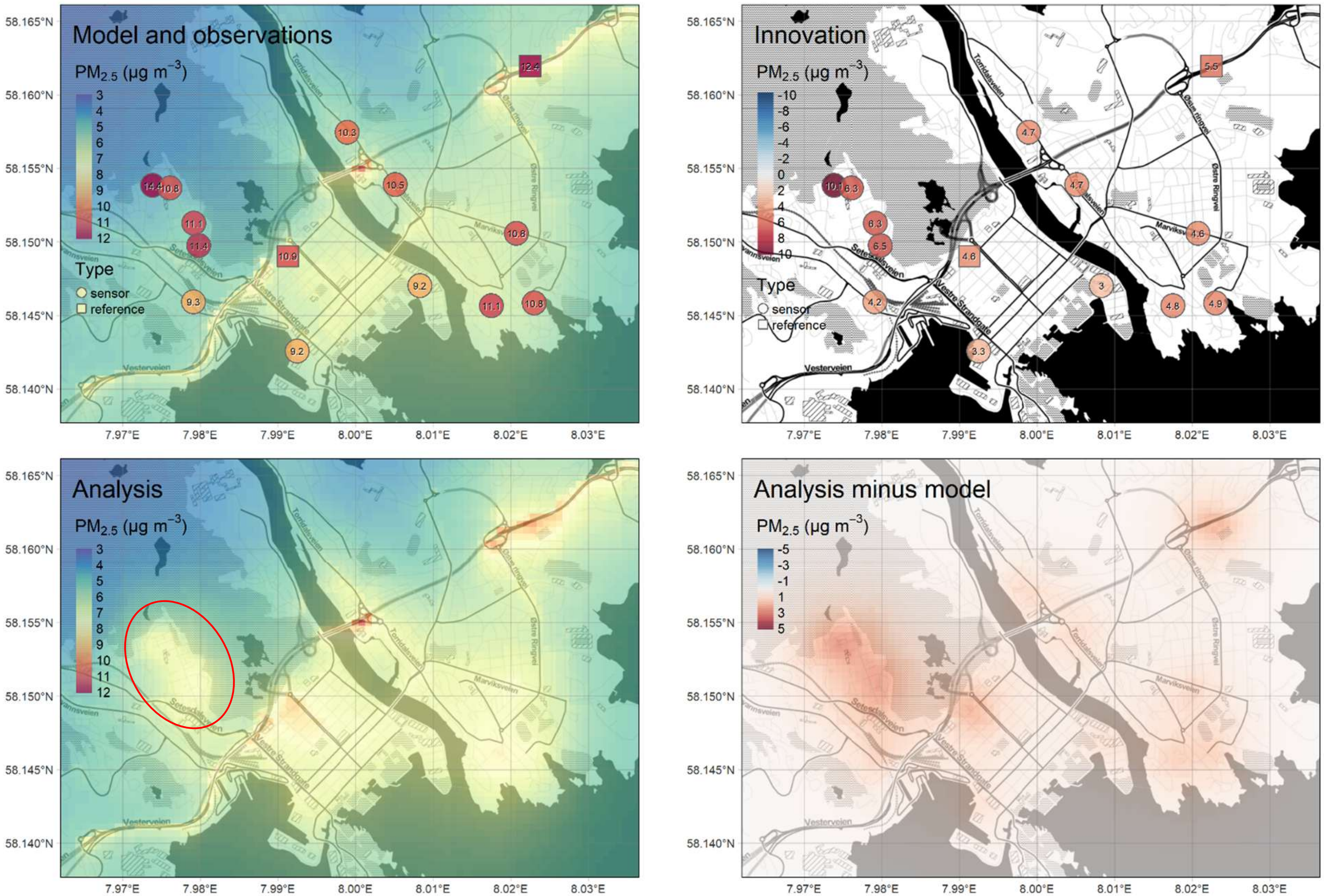

Combining observations of low-cost sensor systems with uEMEP model information through data assimilation, here shown for $PM_{2.5}$ for the period of 2020-12-01 through 2021-02-28 in the city of Kristiansand, Norway.

Hassani, A., Schneider, P., Vogt, M., & Castell, N. (2023). Low-Cost Particulate Matter Sensors for Monitoring Residential Wood Burning. *Environmental Science & Technology*, *57*(40), 15162-15172.

Metric	Before assimilation	After assimilation	Relative change
Mean bias	4.0 µg m^{-3}	1.7 µg m^{-3}	-56 %
RMSE	4.3 µg m^{-3}	2.2 µg m^{-3}	-51 %
MAE	4.0 µg m^{-3}	1.9 µg m^{-3}	-52 %

Results from a leave-one-out cross validation exercise for the Kristiansand case study.

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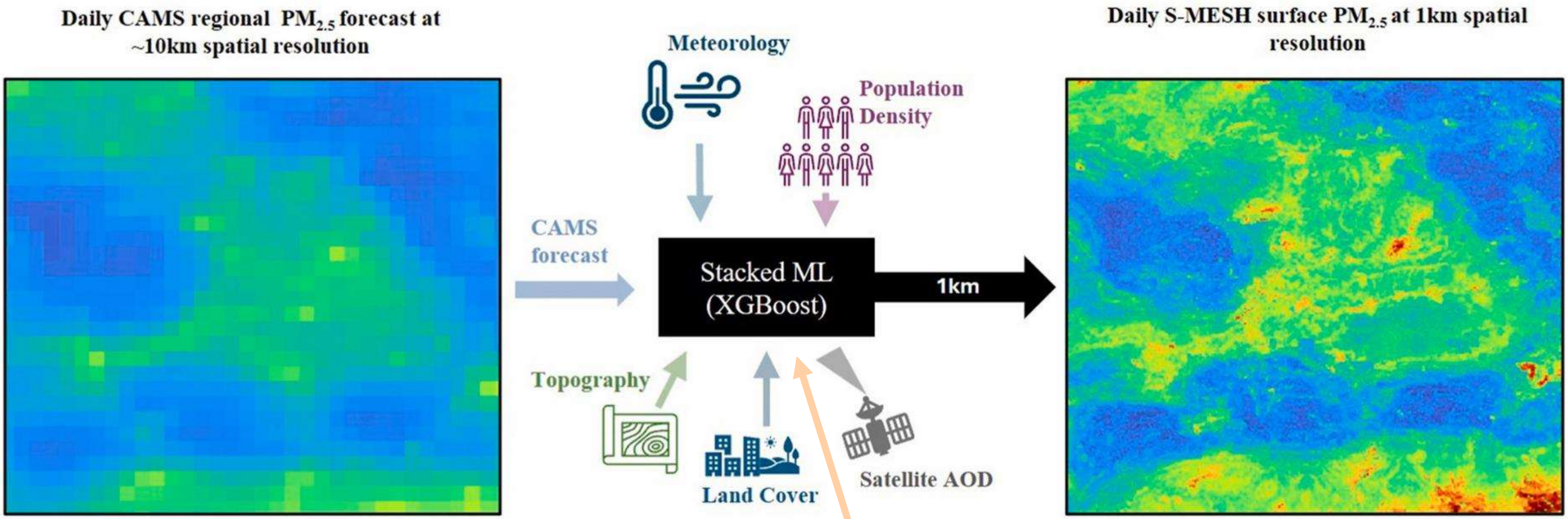
Mapping regional-scale air quality:
Machine Learning

S-MESH: Synergy of Earth Observation and Machine Learning for Air Quality Monitoring in Europe

Simultaneous bias correction and downscaling of the CAMS regional ensemble



CAMS: RMSE = 7.42 μg/m3; MAE = 4.18 μg/m3; R^2 = 0.39

NEW: Sensor observations

S-MESH: RMSE = 6.13 μg/m3; MAE = 3.54 μg/m3; R^2 = 0.58

Shetty, S., Hamer, P. D., Stebel, K., Kylling, A., Hassani, A., Berntsen, T. K., & Schneider, P. (2025). Daily high-resolution surface $PM_{2.5}$ estimation over Europe by ML-based downscaling of the CAMS regional forecast. Environmental Research, 264, 120363.

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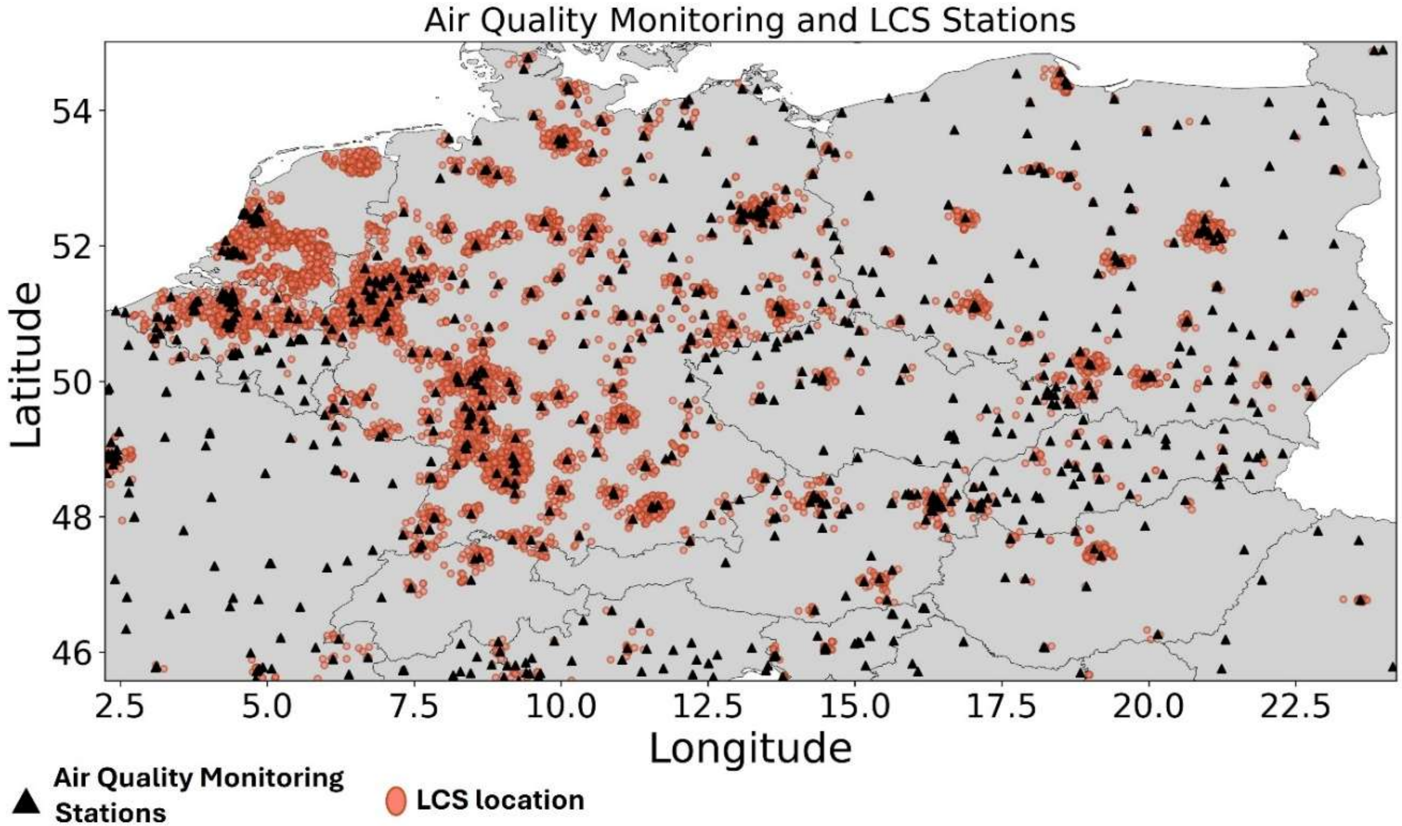
We integrate in S-MESH quality-controlled (Hassani et al., 2025) observations from large-scale low-cost $PM_{2.5}$ sensor networks (sensor.community and PurpleAir), providing high-density in-situ measurements.



The study domain overlaid with the locations of the available **quality-controlled LCS measurements** (Sensor.Community and PurpleAir) from Hassani et al. (2025) and the air quality monitoring stations used for training and testing

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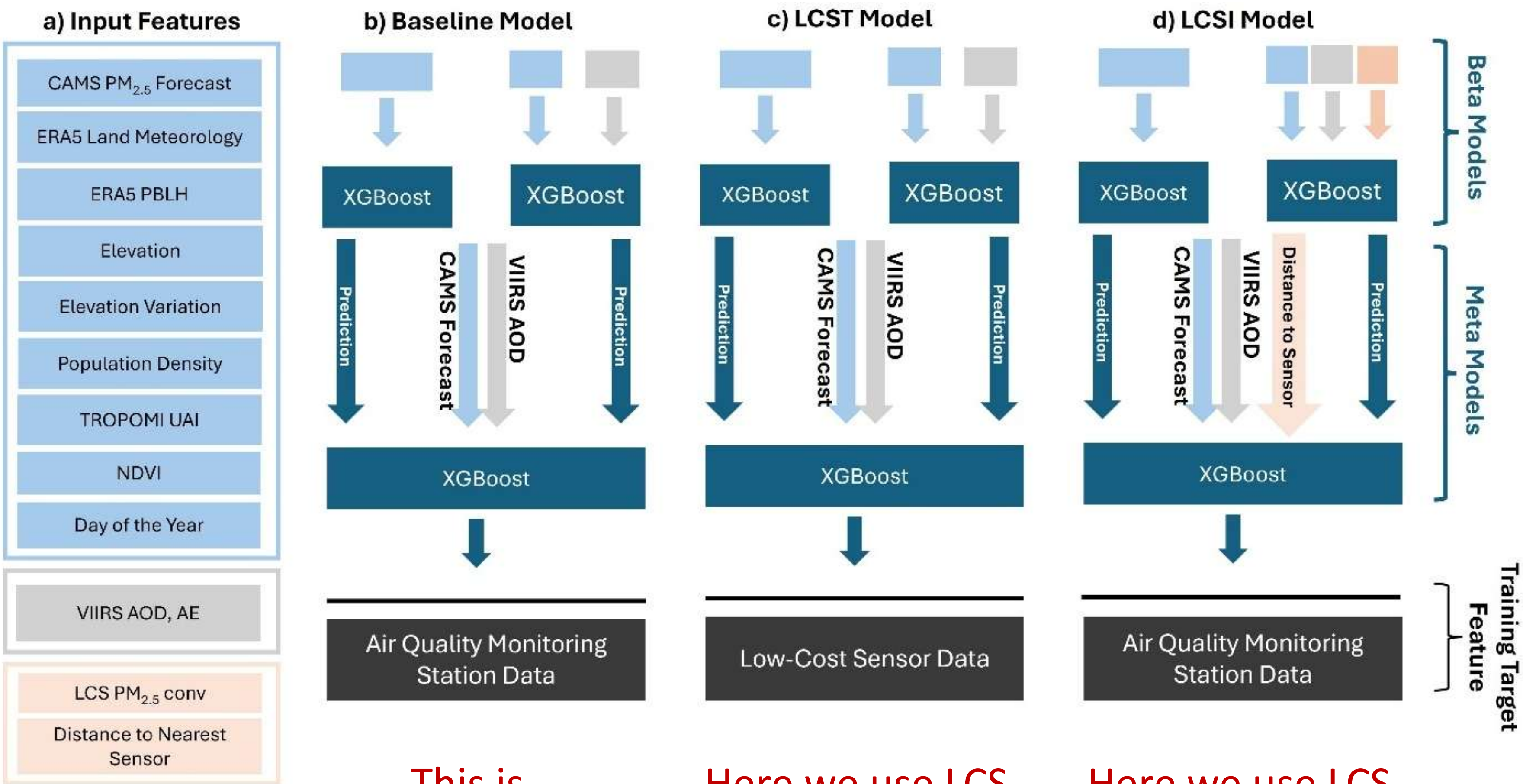

This is without LCS data

Here we use LCS data for training (LCST)

Here we use LCS data as input (LSCI)

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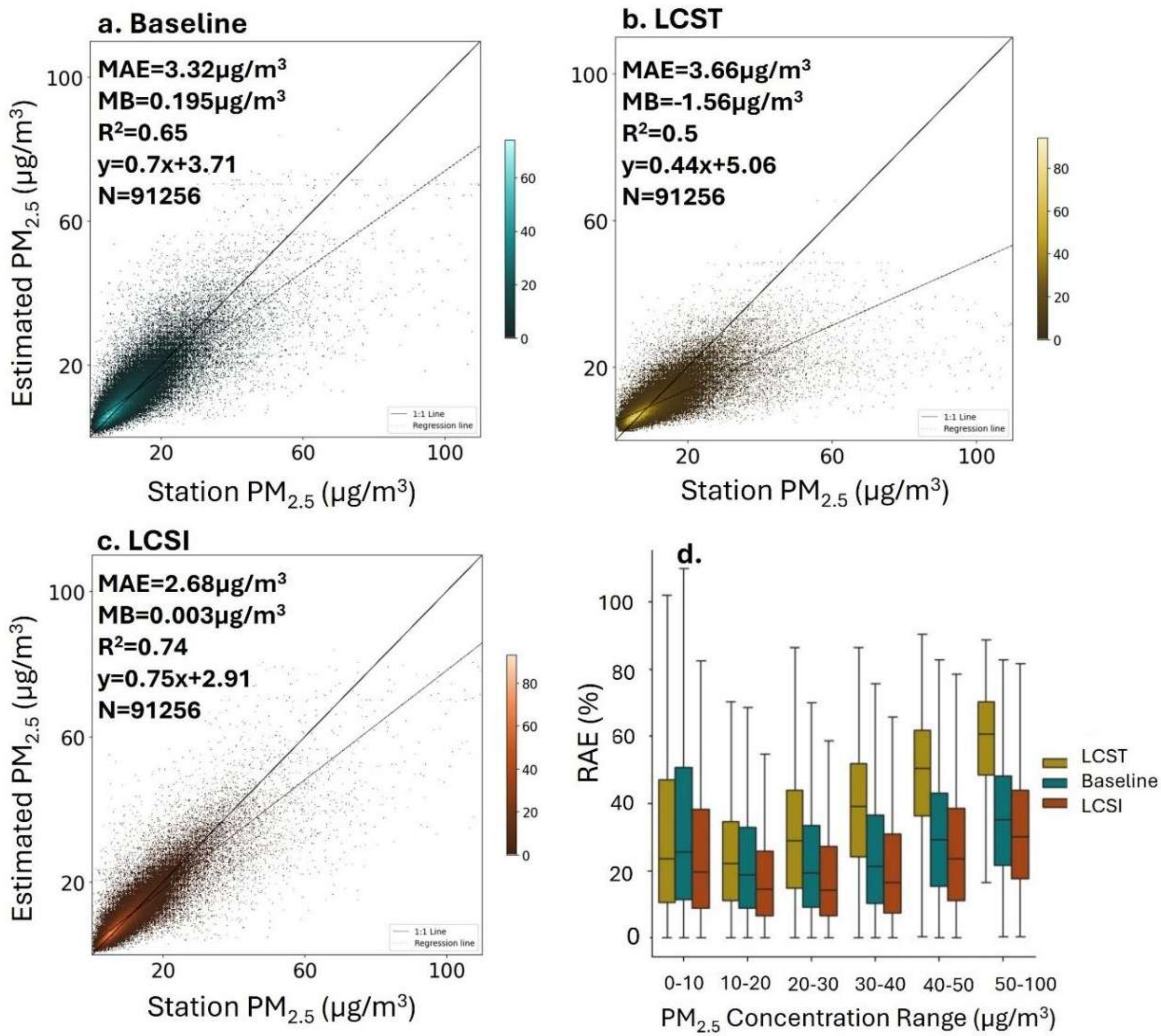
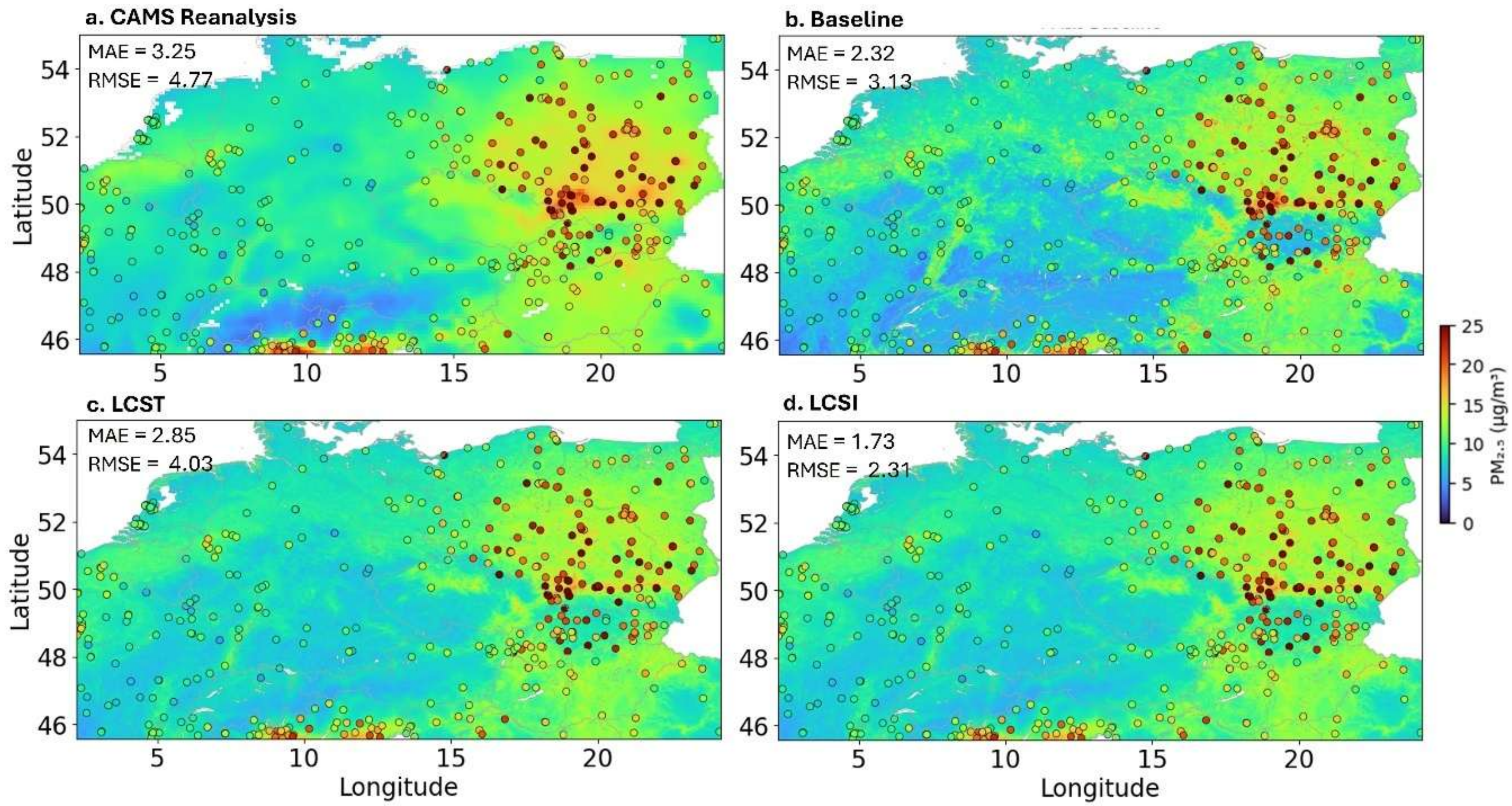
Overall model performance of daily estimates using test datasets for the years 2021-2022, depicted for the 3 different models.



We find that a **LCS-convolution layer** as additional input to the stacked ML model **shows substantially improved accuracy over the CAMS reanalysis.**

CAMS regional reanalysis

S-MESH without LCS



S-MESH with LCS for training

S-MESH with LCS as input feature

Shetty, S., Hassani, A., Salamalikis, V., Hamer, P. D., Stebel, K., Kylling, A., Castell, N., Berntsen, T. K., & Schneider, P. (2026). Large scale sensor networks improve continental scale PM2.5 monitoring. Manuscript in review at Environmental Research.

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Take-home messages

1. The **FILTER framework** (Hassani et al. 2025) and accompanying code **allows LCS quality control in a robust and transparent manner,** which is a requirement for most LCS applications
2. On the city scale we **combine high-resolution AQ models with LCS data** (Schneider et al., 2023) using traditional data assimilation techniques for **improved high-resolution mapping of air quality**
3. **Machine learning-based fusion approaches such as S-MESH** (Shetty et al. 2025) allow using LCS networks for **regional-scale AQ mapping**. We see a **substantial improvement in accuracy** when sensor observations are integrated as a convolution layer.

Hassani, A., Salamalikis, V., Schneider, P., Stebel, K., and Castell, N.: A scalable framework for harmonizing, standardization, and correcting crowd-sourced low-cost sensor PM2.5 data across Europe, Journal of Environmental Management, 380, 125100, https://doi.org/10.1016/j.jenvman.2025.125100, 2025.

Schneider, P., Vogt, M., Haugen, R., Hassani, A., Castell, N., Dauge, F. R., and Bartonova, A.: Deployment and Evaluation of a Network of Open Low-Cost Air Quality Sensor Systems, Atmosphere, 14, 540, https://doi.org/10.3390/atmos14030540, 2023.

Shetty, S., Hassani, A., Salamalikis, V., Hamer, P. D., Stebel, K., Kylling, A., Castell, N., Berntsen, T. K., & Schneider, P. (2025). Large scale sensor networks improve continental scale PM2.5 monitoring. Manuscript in review at Environmental Research.

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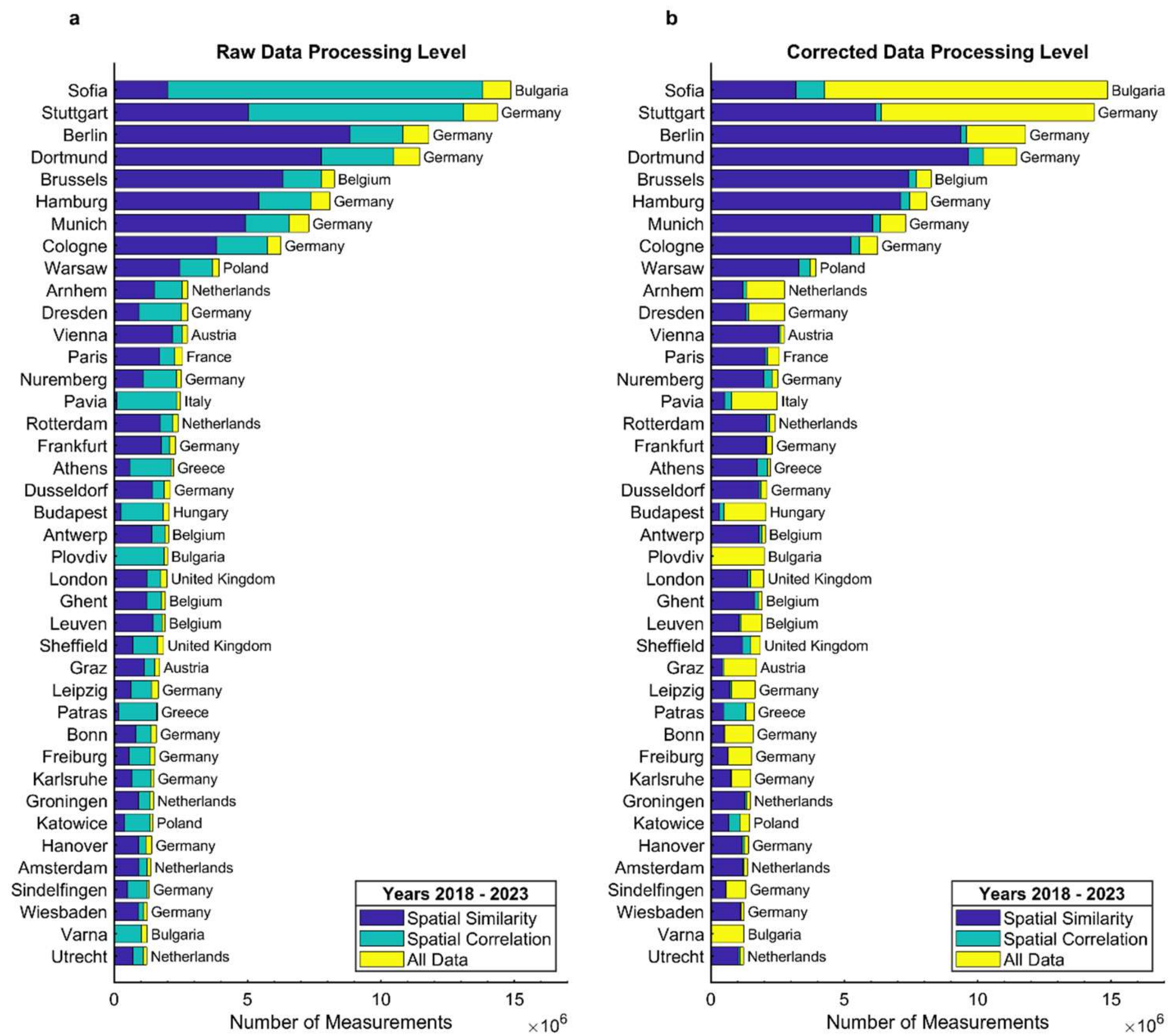
Extra slides

Data loss



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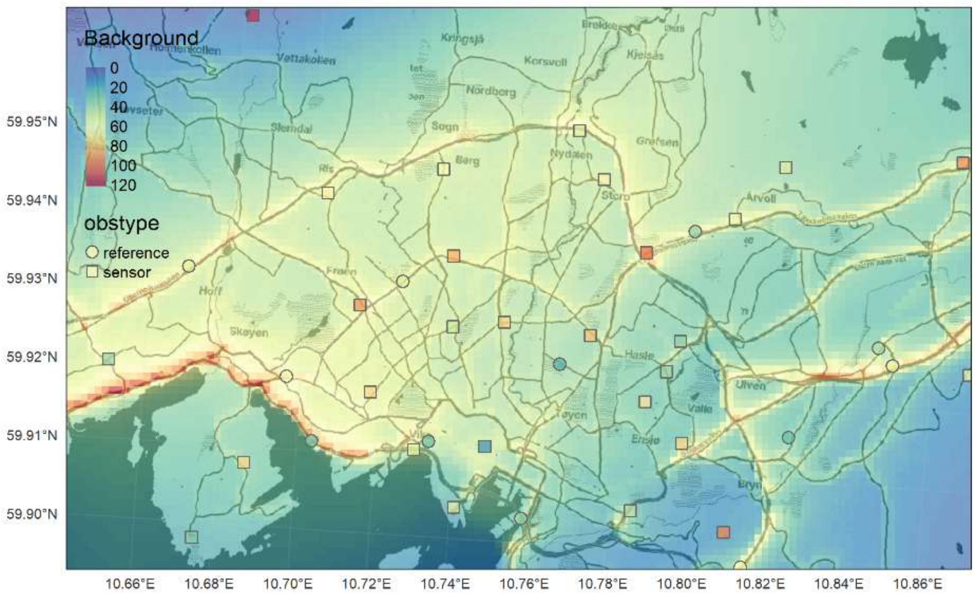
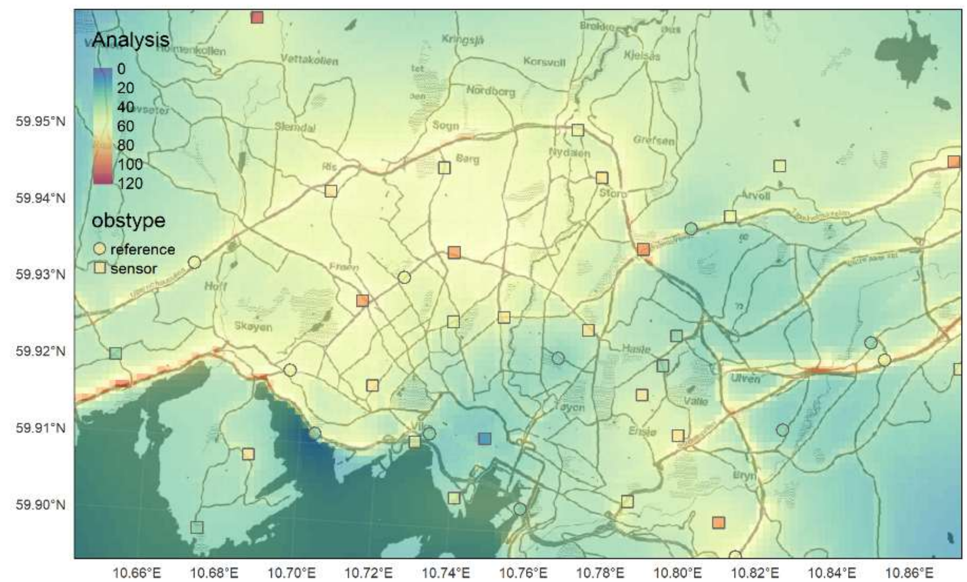
Effect of data assimilation for mapping

Before assimilation



After assimilation



Example of integration of LCS network, reference stations, and uEMEP model for NO_2 using data assimilation, shown here for 2023-03-15 at 10:00 UTC.