

European Network on New Sensing Technologies for Air Pollution Control and Environmental Sustainability - *EuNetAir*

COST Action TD1105

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New Sensing Technologies for Air Quality Monitoring

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Mapping Urban Air Quality using Low-Cost Sensors: Opportunities and Challenges

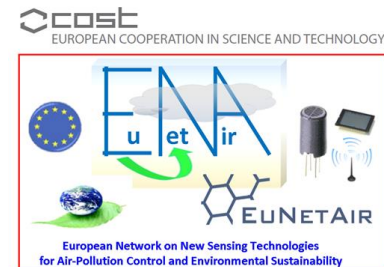


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Mapping Urban Air Quality using Low-Cost Sensors: Opportunities and Challenges

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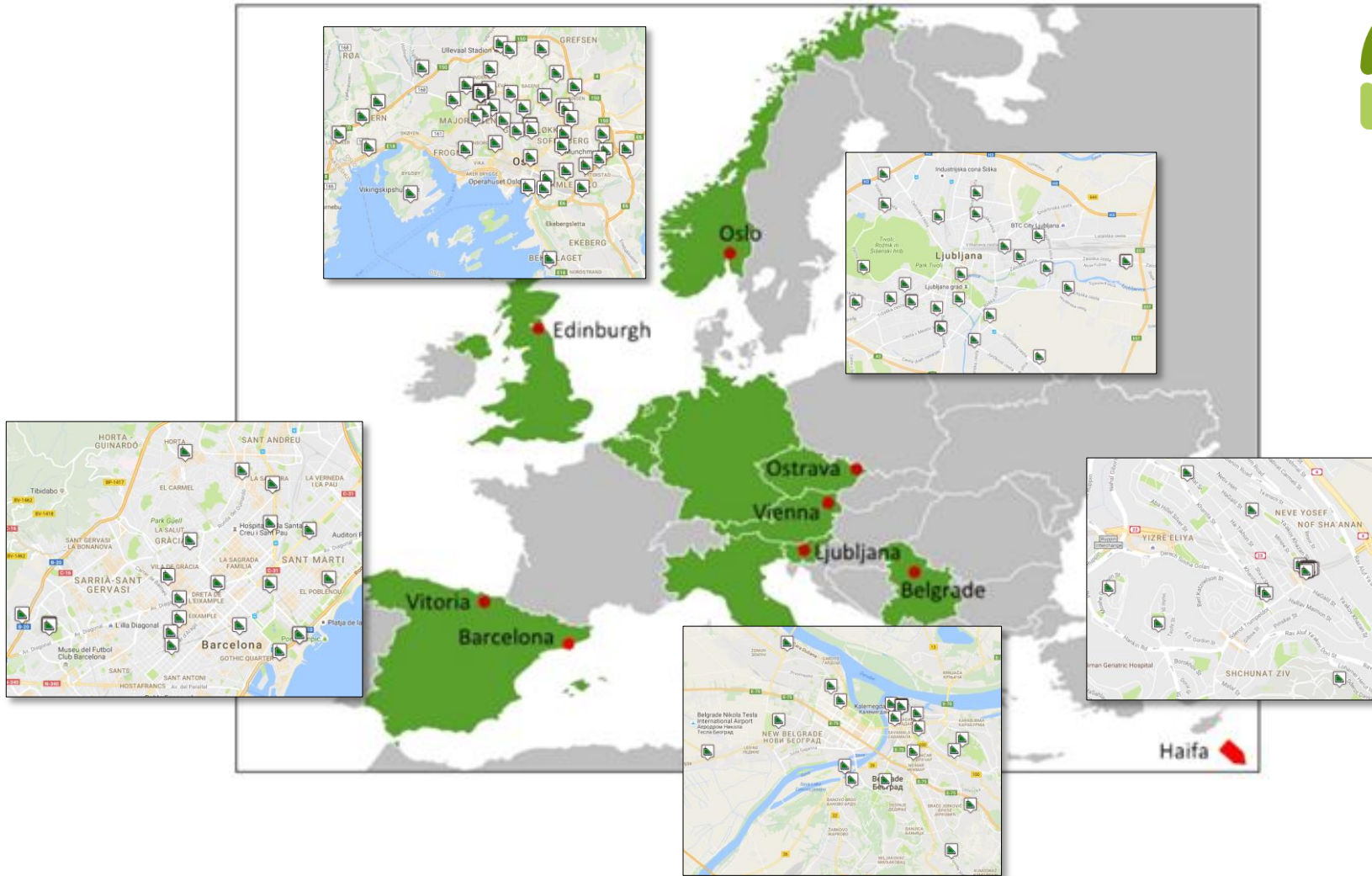


Introduction

- **Low-cost microsensors** can provide air quality measurements throughout the city at much **higher density** than is possible with traditional reference equipment
- This opens the opportunity for creating unprecedented **high-resolution urban-scale maps** of air quality based on observations
- Such maps can then be used to **provide citizens** with a **wide variety of services**, e.g. health-aware routing, personal exposure etc.
- To achieve this we need to **combine the sensor observations with model information** (either dispersion or land-use regression) to map concentrations onto a high-resolution grid



Deployment throughout Europe





This CITI-SENSE portal was developed with contribution from the European union About project

LOCATION Oslo



TIME PERIOD

LAYERS

FILTERS

FOR LEO USERS

City APIN

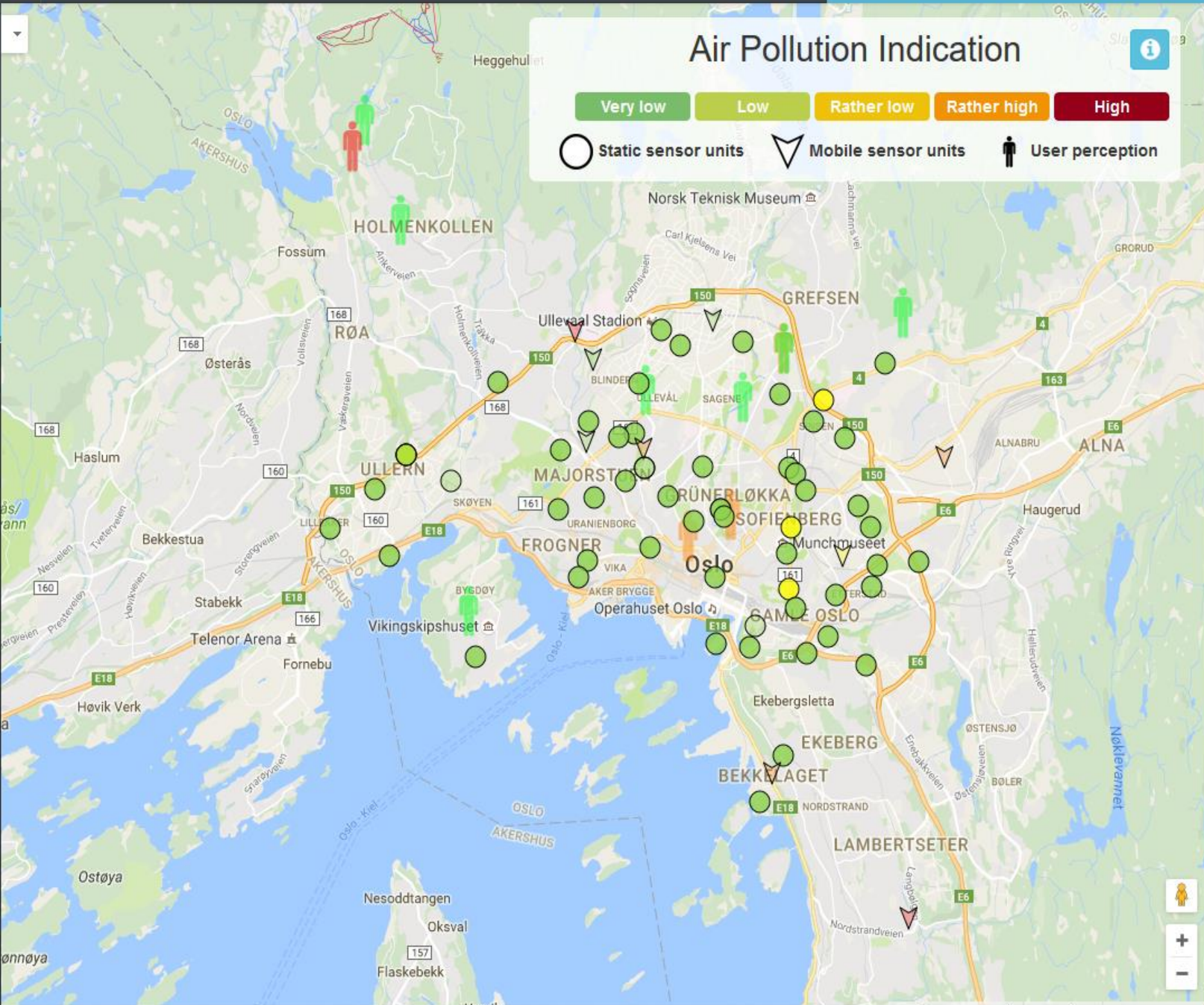
City Perception

Give your opinion

Air Pollution Indication

Very low Low Rather low Rather high High

Static sensor units Mobile sensor units User perception



Mapping Methodology

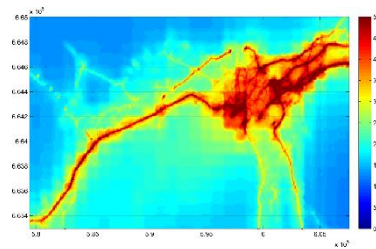
- Theoretical basis

- Data fusion is a subset of data assimilation techniques (Lahoz and Schneider, 2014)
- We use geostatistical framework: Universal kriging approach
- Analysis performed entirely in log-space
- Explicit automated modelling of spatial autocorrelation

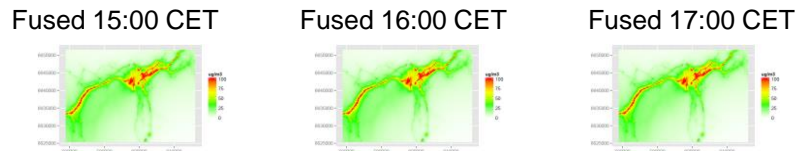
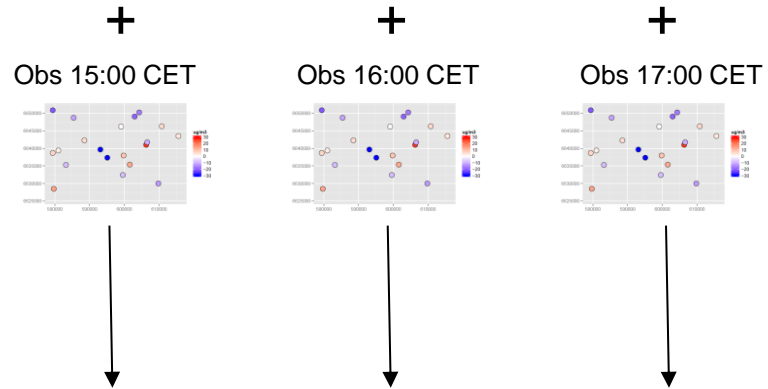
- In practice

- Create static basemap for each mapping location
- Retrieve crowdsourced sensor observations at each hour
- Modify basemap based on latest observations using geostatistical data fusion
- Final result are hourly maps with the current best guess for the $\text{NO}_2/\text{PM}_{10}/\text{PM}_{2.5}$ concentration field at all locations

Static basemap
(for each species and location)



Basemap:
Provides information about general spatial patterns



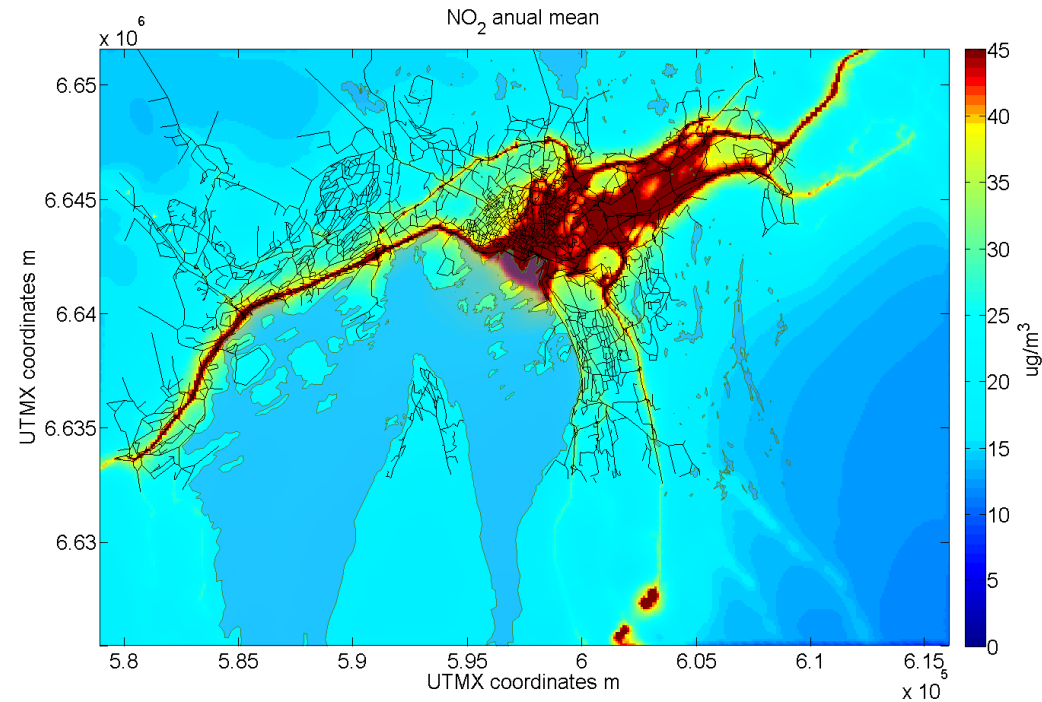
Geotech observations:
Provide information about current state of atmosphere at a few sampling locations

Fused map:
Value-added product providing a best guess of current state of atmosphere for the entire domain

Lahoz, W. A., and P. Schneider (2014), Data assimilation: making sense of Earth Observation, *Front. Environ. Sci.*, 2(16), 1–28, doi:10.3389/fenvs.2014.00016.

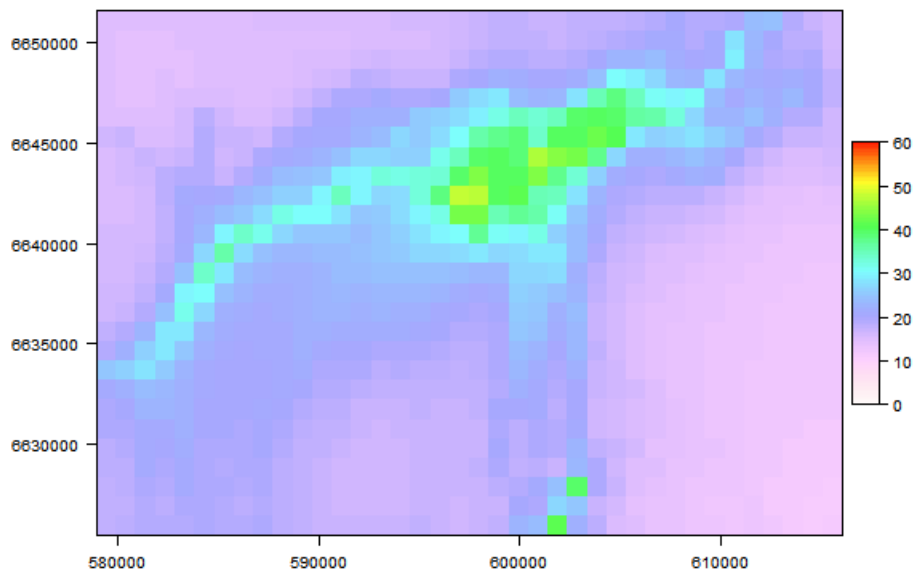
Modelling of the basemaps

- Can be nearly any spatially exhaustive dataset that is related to the observation
- Best to use are urban-scale dispersion models
- Alternatively concentration map created through LUR modelling
- We use the EPISODE model
 - Three-dimensional, combined Eulerian/Lagrangian air pollution dispersion model, developed at NILU
 - Combined modelling and postprocessing approach to obtain basemaps at 10-100 m spatial resolution

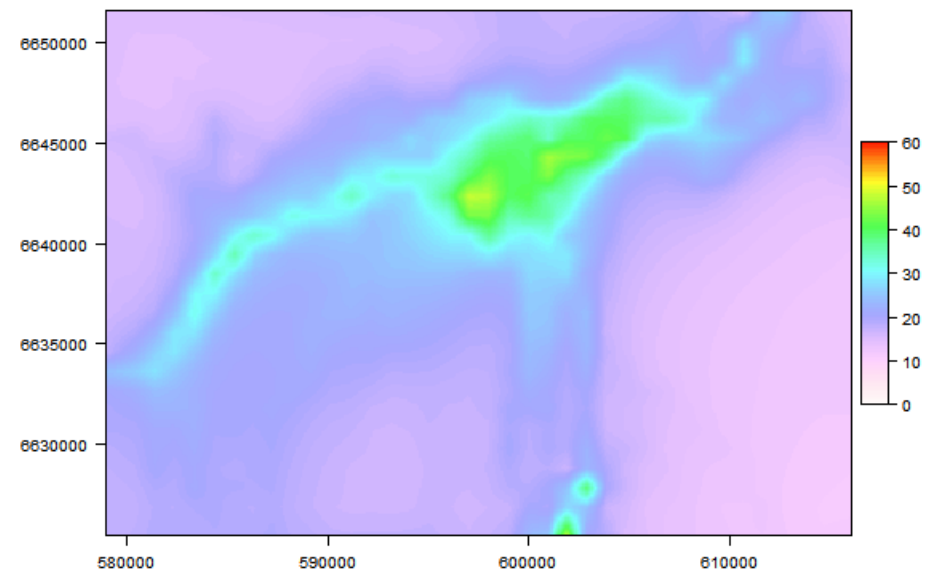


High-resolution map of NO₂ in Oslo from the EPISODE dispersion model. These kind of maps are ideally suited as a spatially distributed auxiliary dataset.

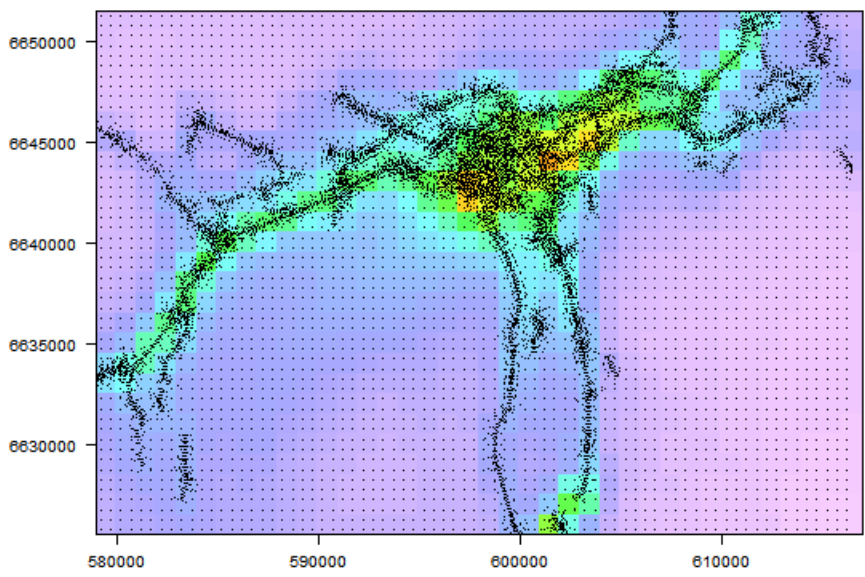
Original EPISODE gridded output



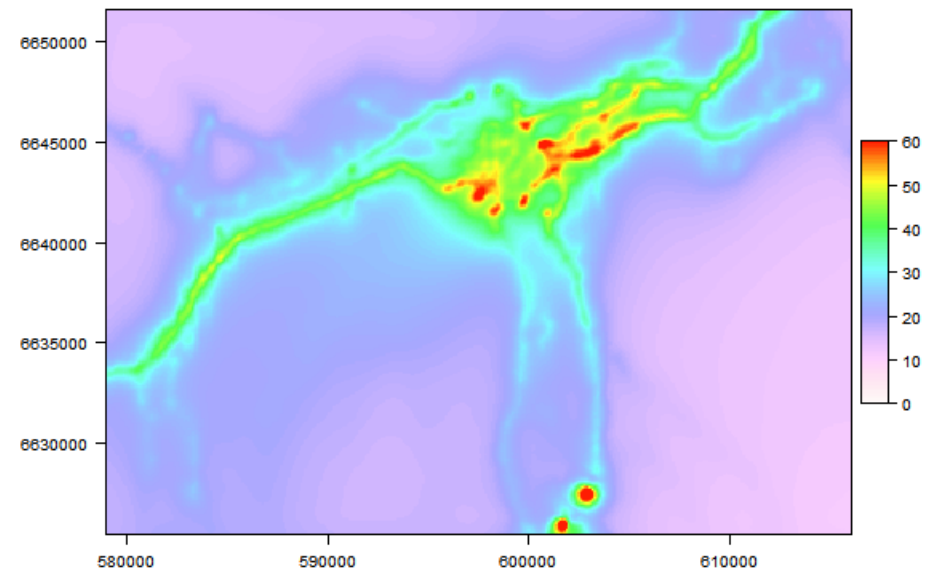
Simple linear interpolation



Distribution of receptor points

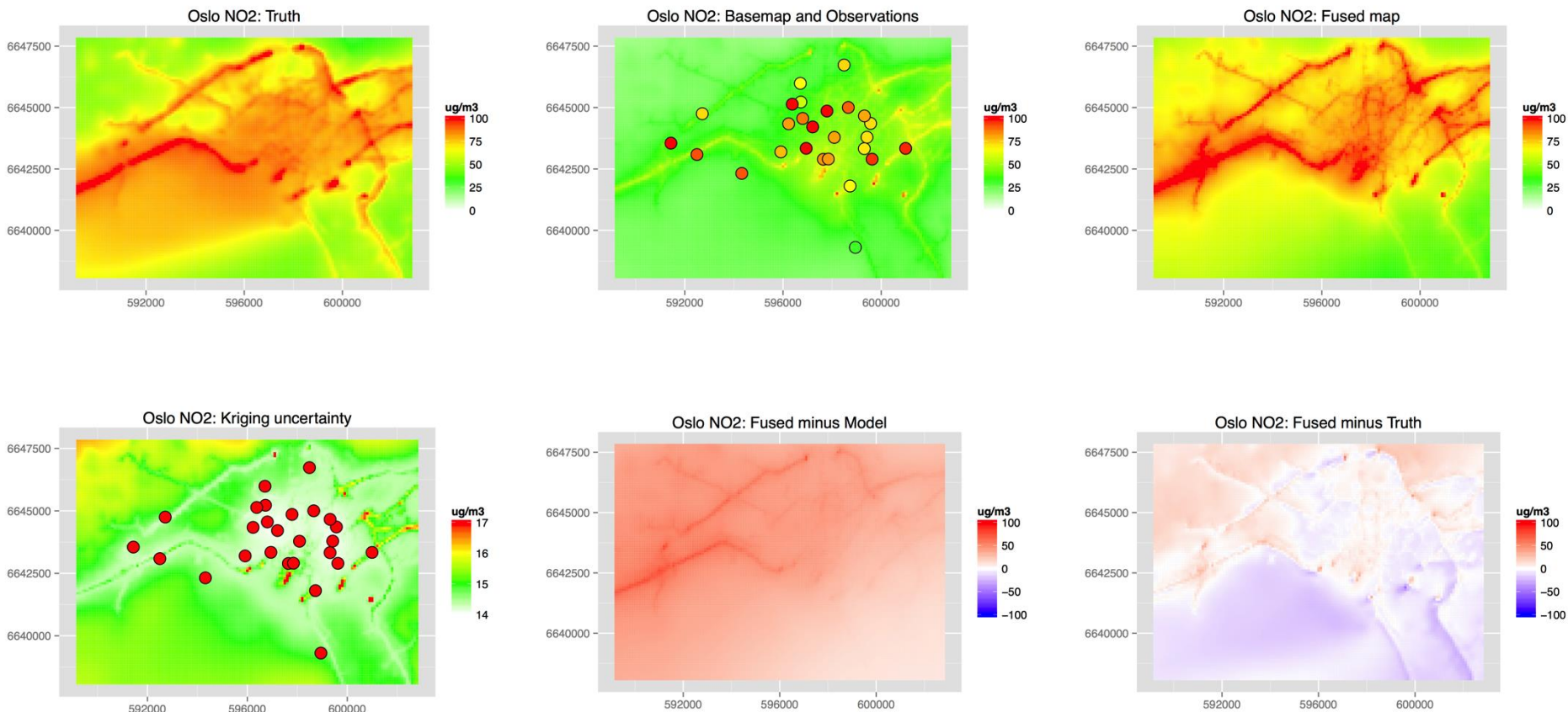


Downscaled using concentrations at receptor points



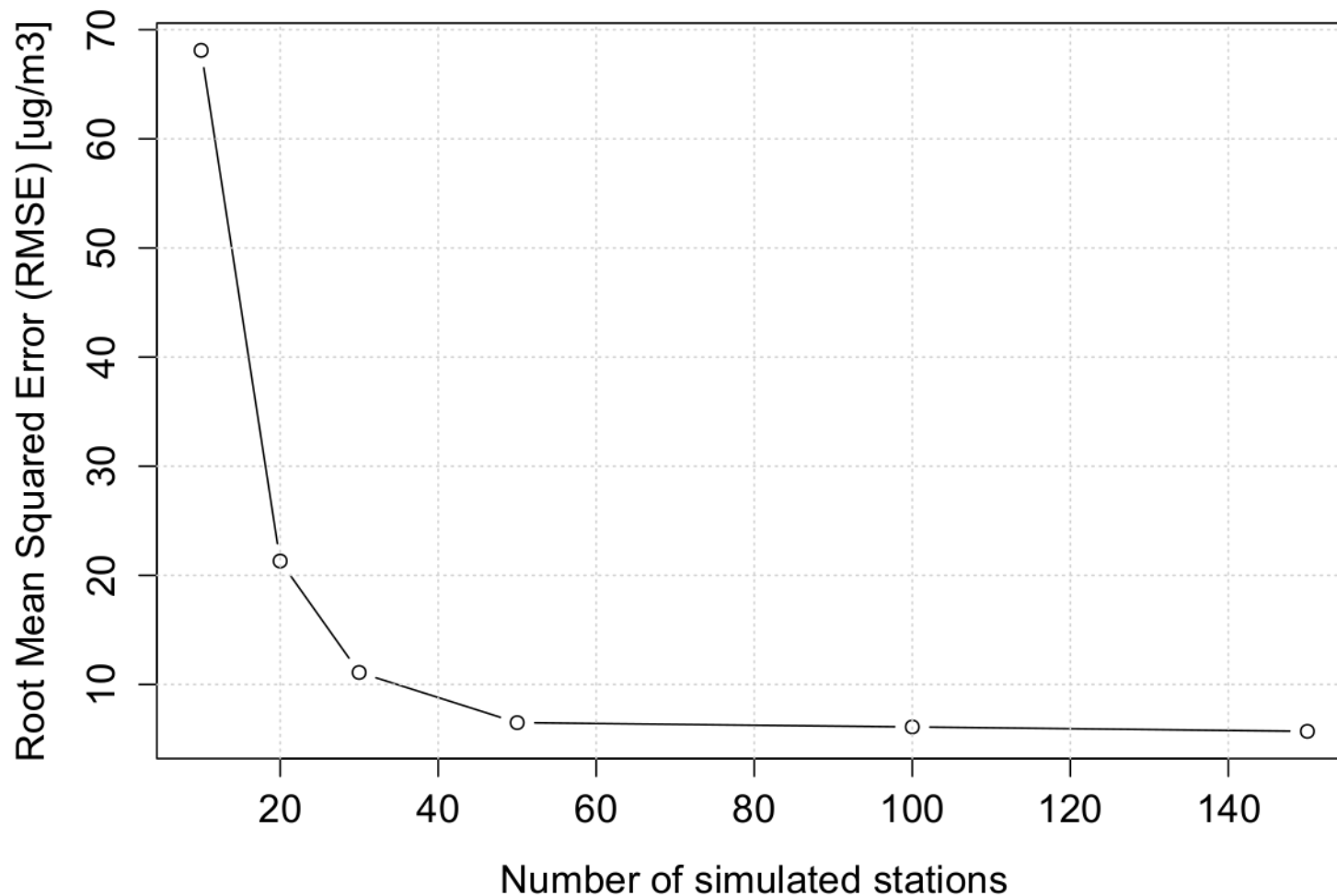
Receptor-point based downscaling of the gridded EPISODE output

A simulated example for Oslo

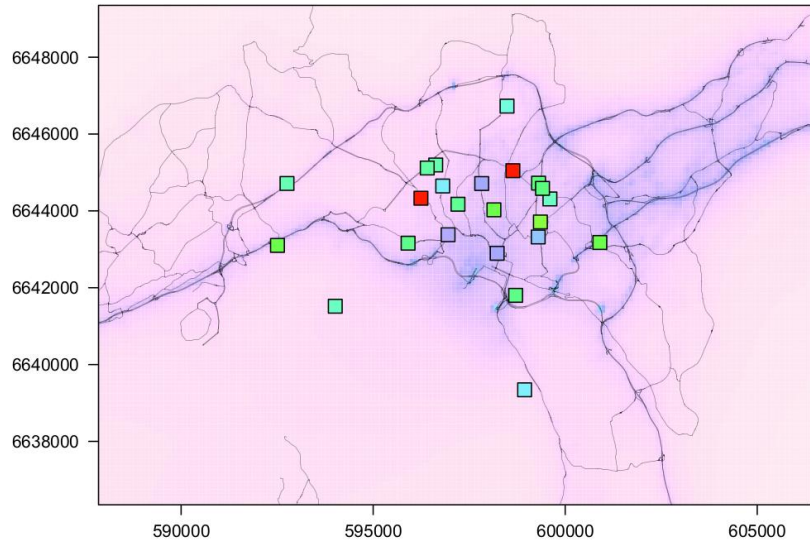


Example of data fusion with simulated observations. Top left panel: “true” NO₂ field (in practice, unknown). Center top panel: model-derived annual average basemap of NO₂ and observations simulated from truth field using a random error. Top right panel: map from data fusion algorithm applied to basemap/observations. Bottom left panel: uncertainty associated with data fusion process. Bottom center/right panels: difference between fused map and model and “truth”, respectively.

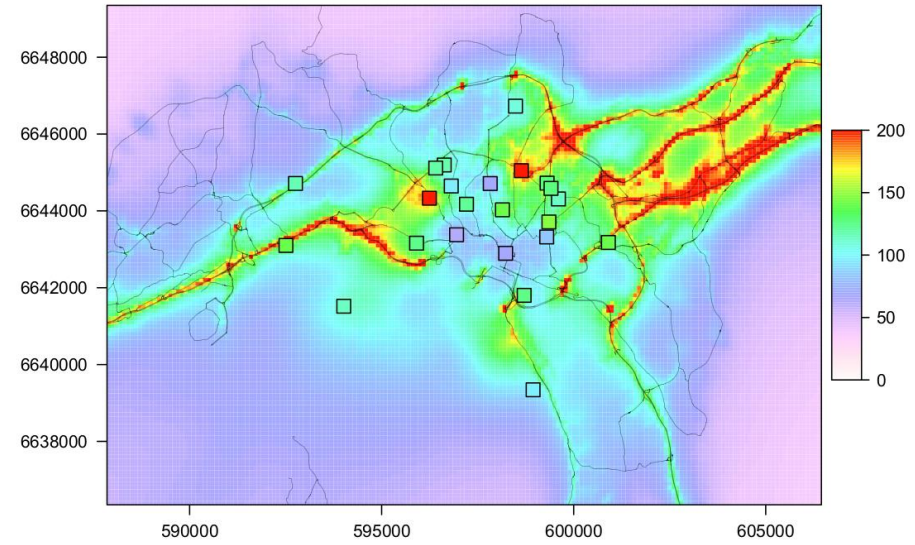
Impact of station number



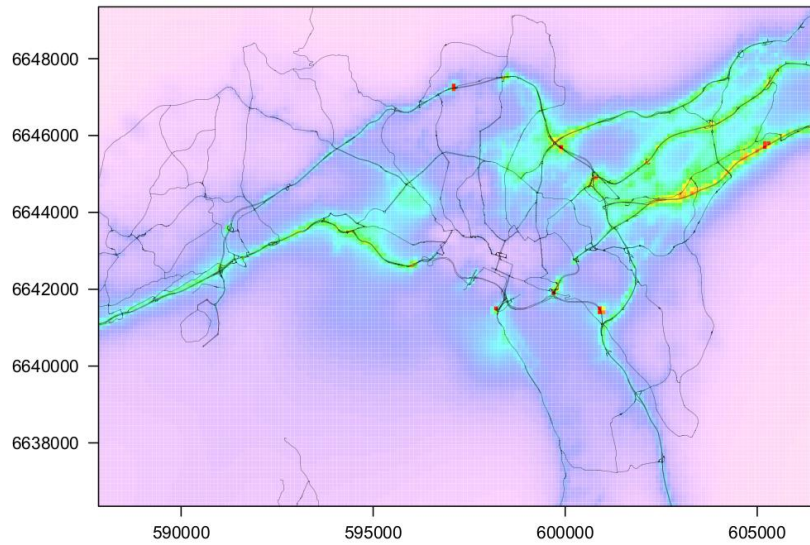
Basemap and observations [ug/m3]



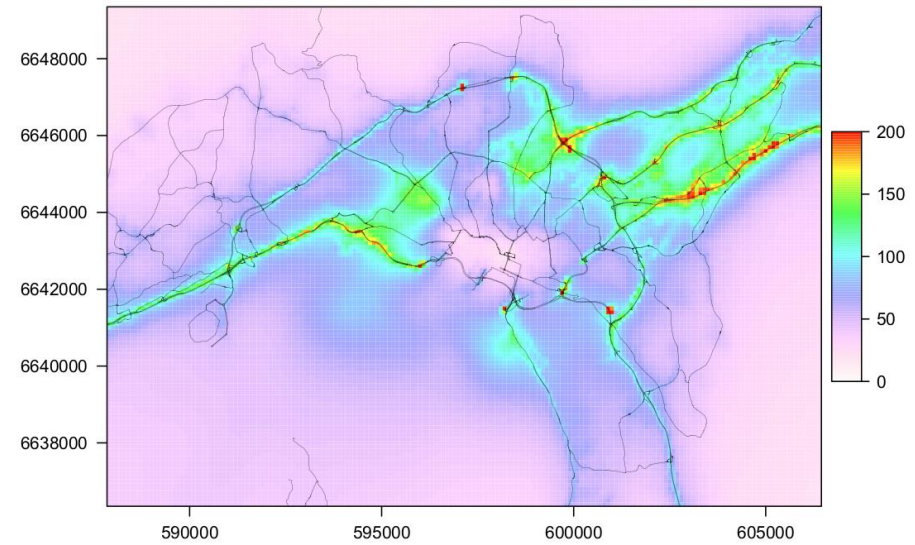
Data fusion result [ug/m3]



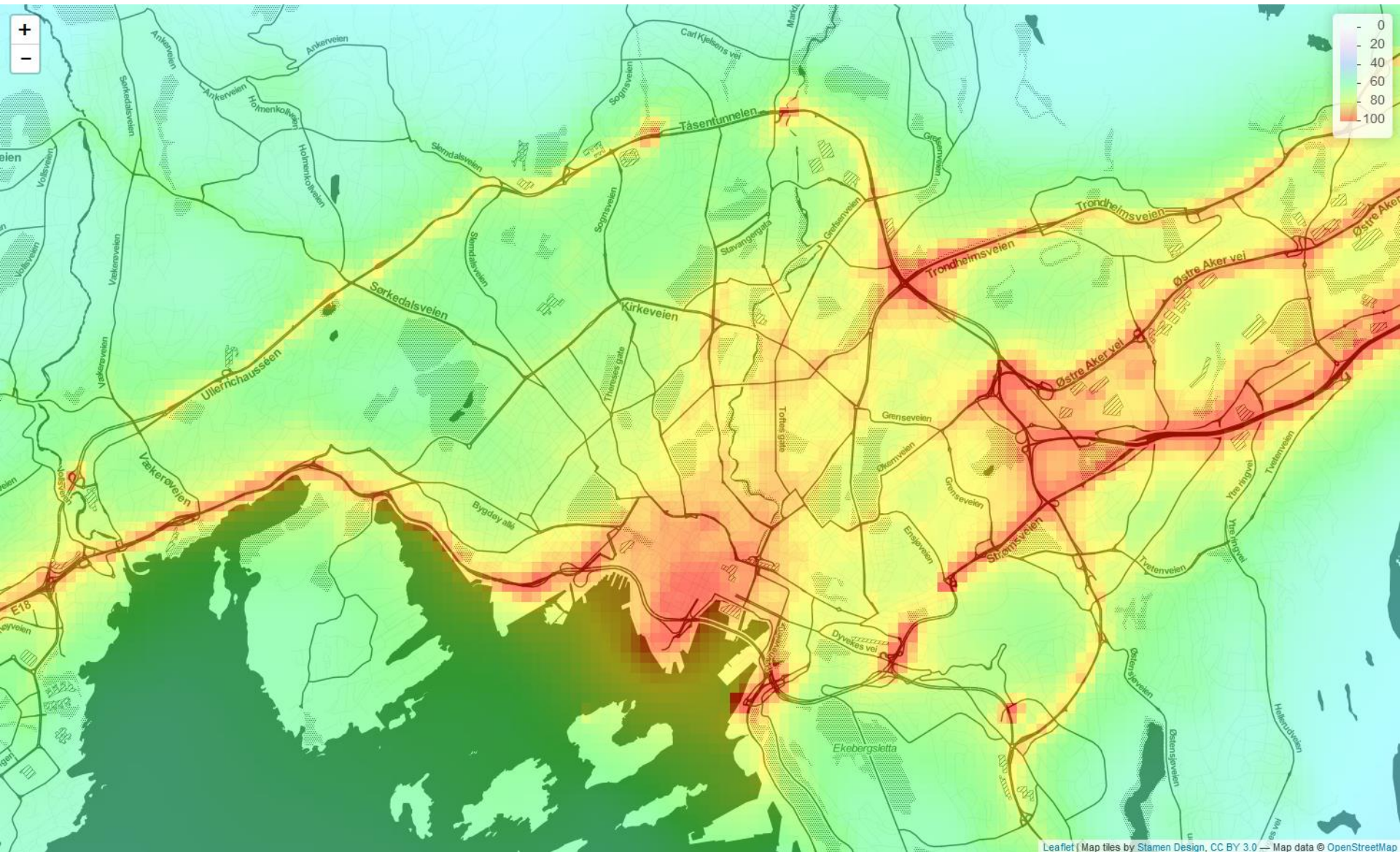
Mapping uncertainty [ug/m3]



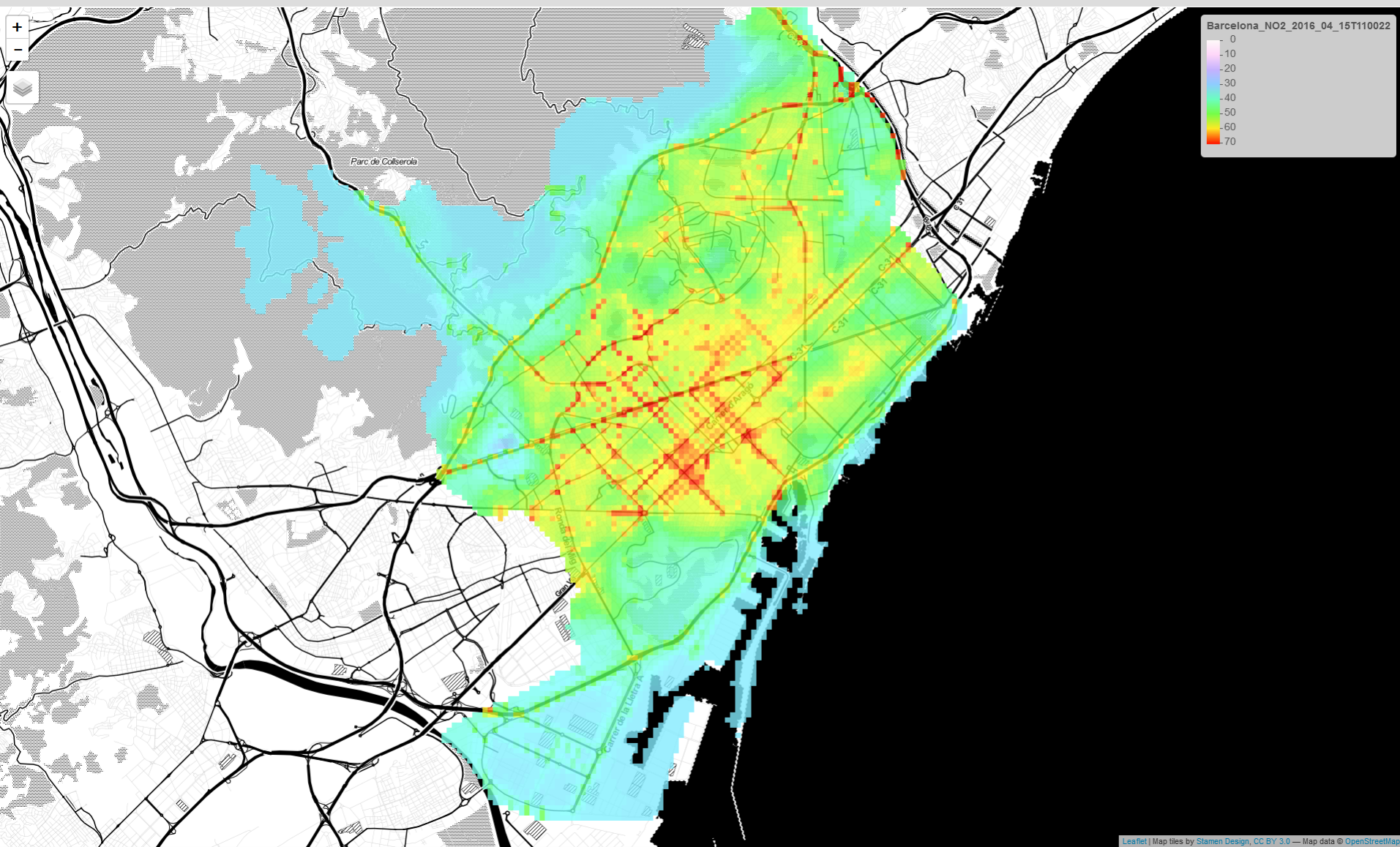
Basemap correction [ug/m3]



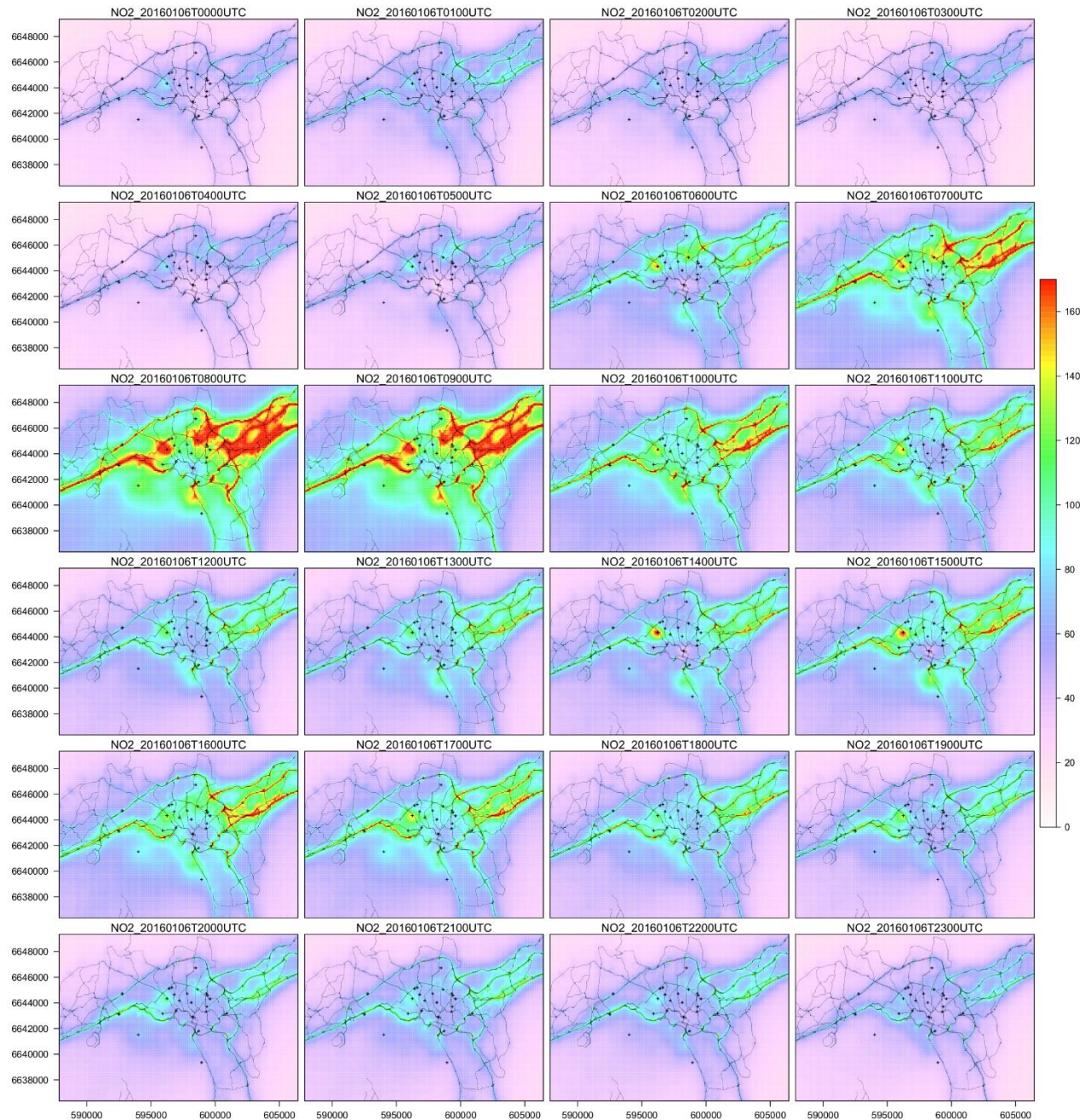
Example of the data fusion process combining crowdsourced observations with a modeled basemap, here shown for NO₂ on 6 January 2016 at 9:00 UTC.



Example of a data fusion-based surface concentration field of NO₂ for Oslo, Norway, at 100 m spatial resolution ([link](#)).

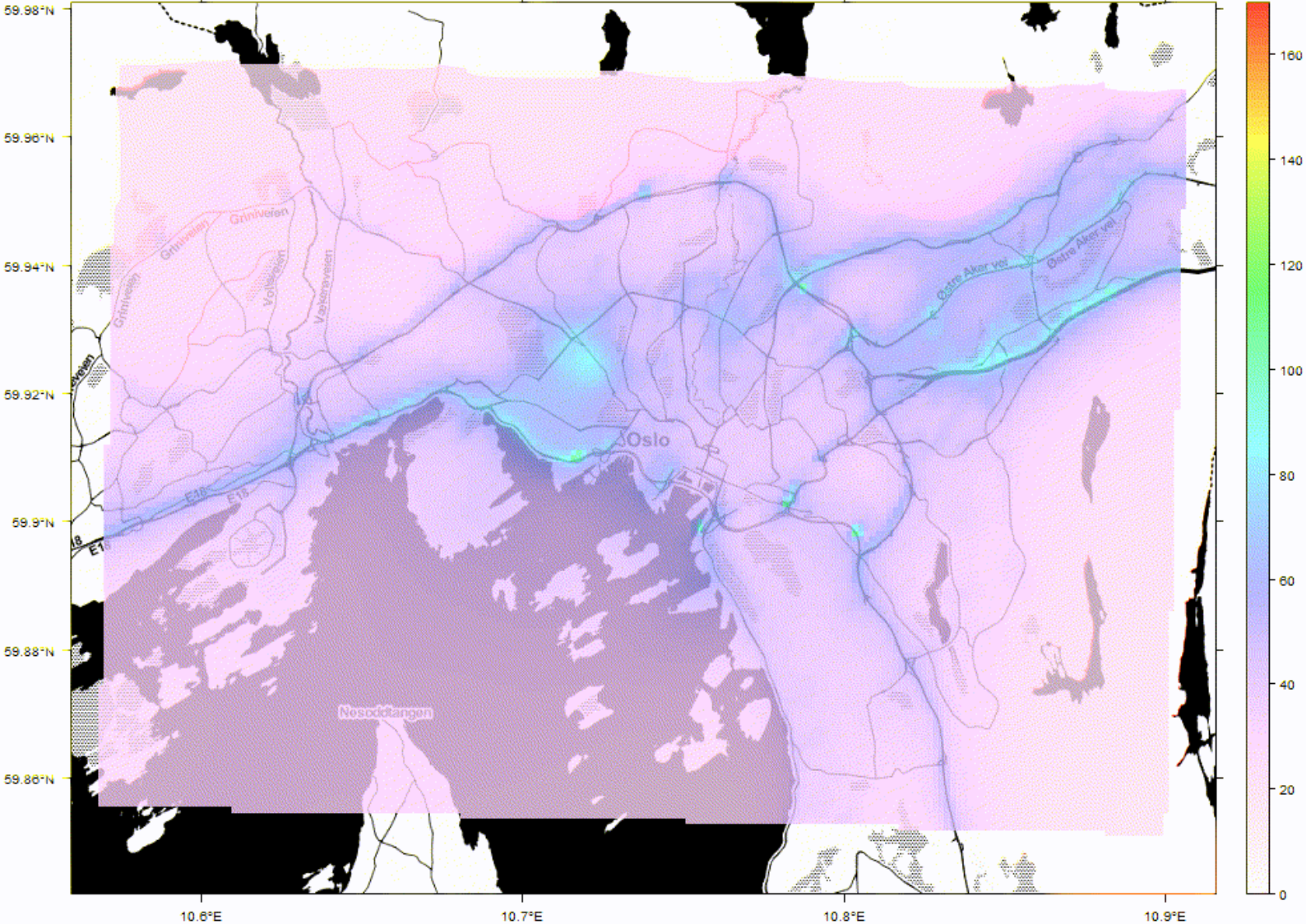


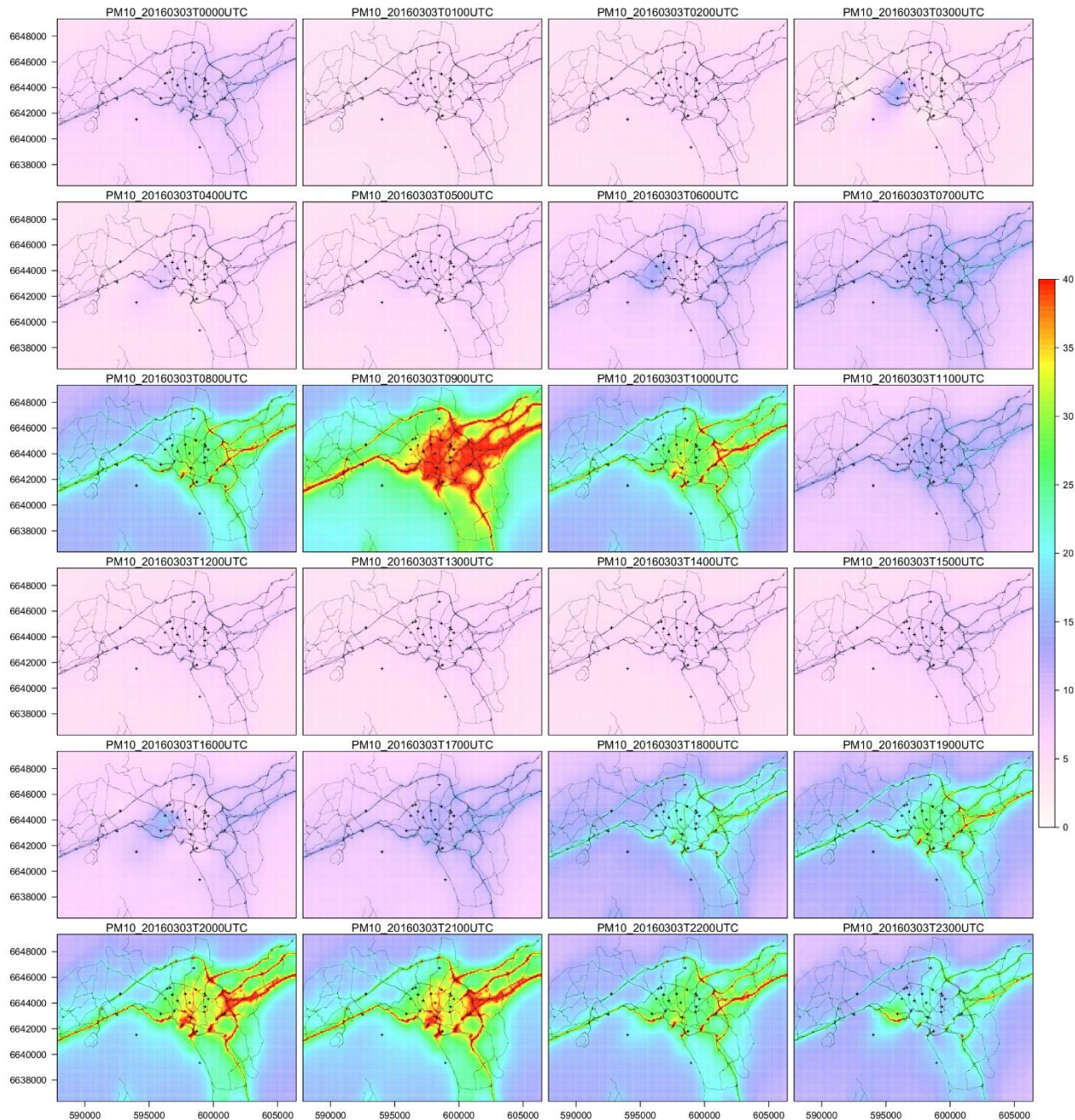
Example of a data fusion-based surface concentration field of NO₂ for Barcelona, Spain, at 100 m spatial resolution ([link](#)).



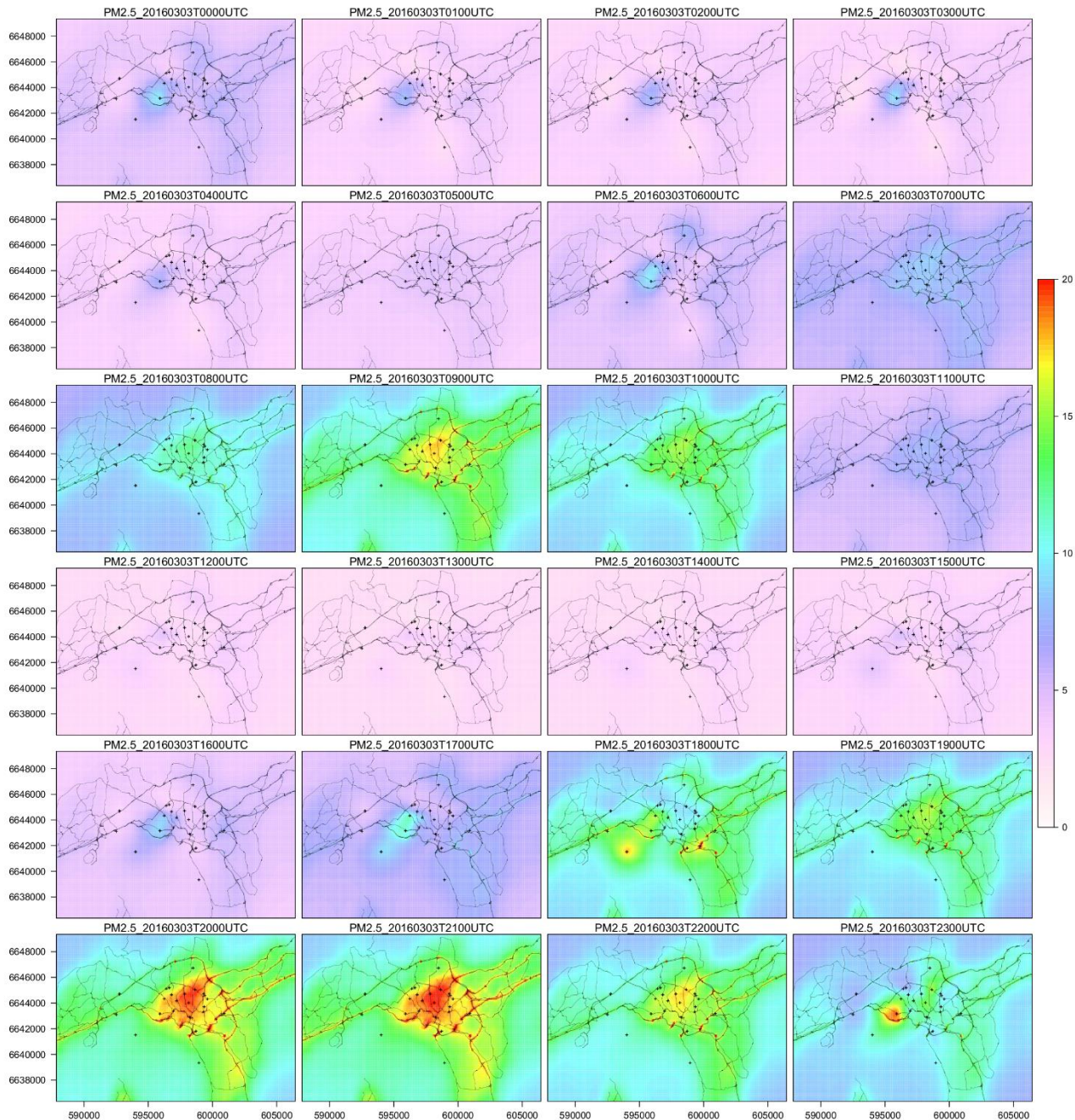
Example of 24 hours of data fusion results in Oslo, combining NO₂ measurements from the AQMesh units with a long-term average basemap derived from the EPISODE model, here shown for 6 January 2016

NO2_20160106T0000.UTC

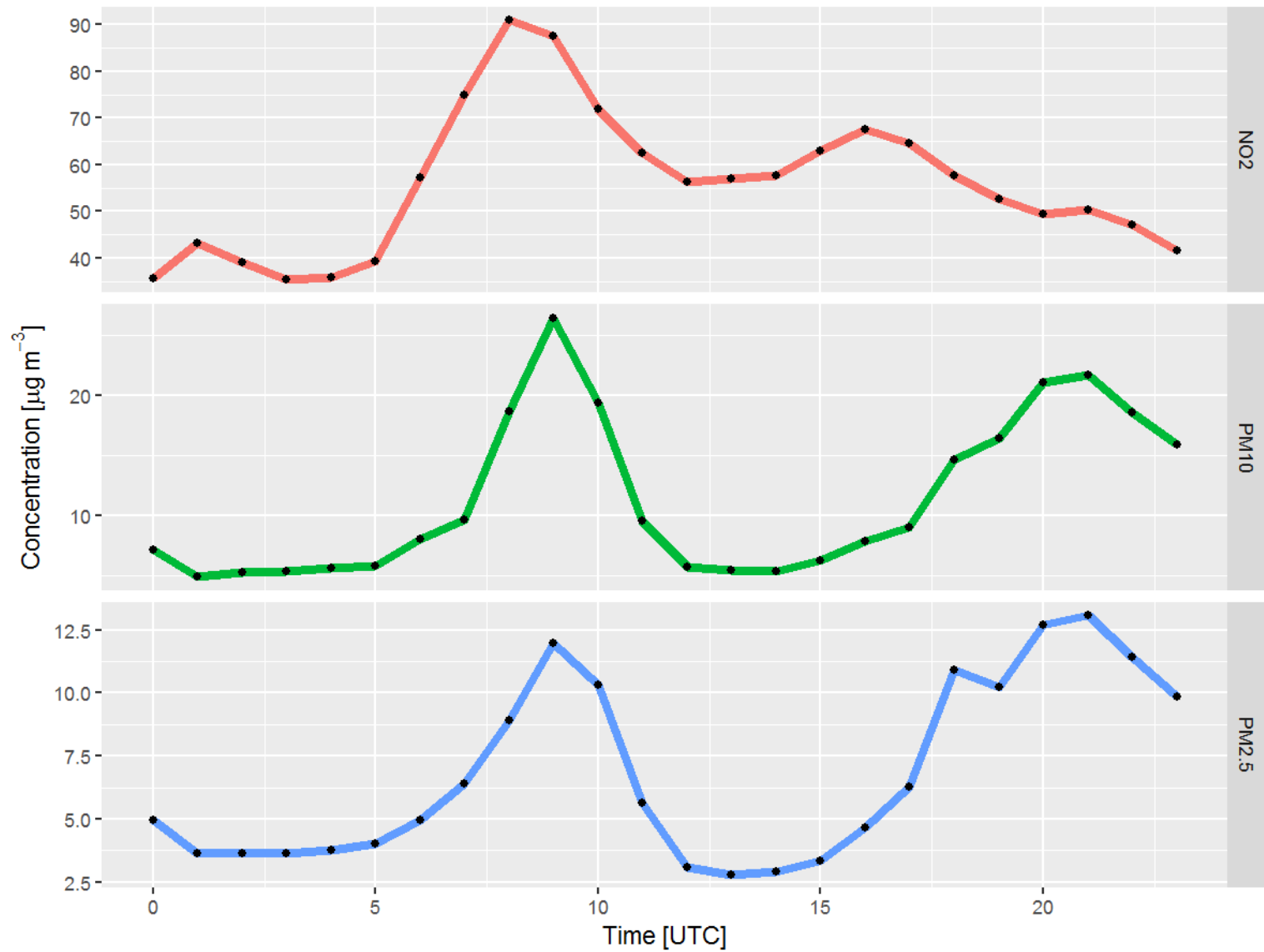




Example of 24 hours of data fusion results in Oslo, combining PM₁₀ measurements from the AQMesh units with a long-term average basemap derived from the EPISODE model, here shown for 22 March 2016.

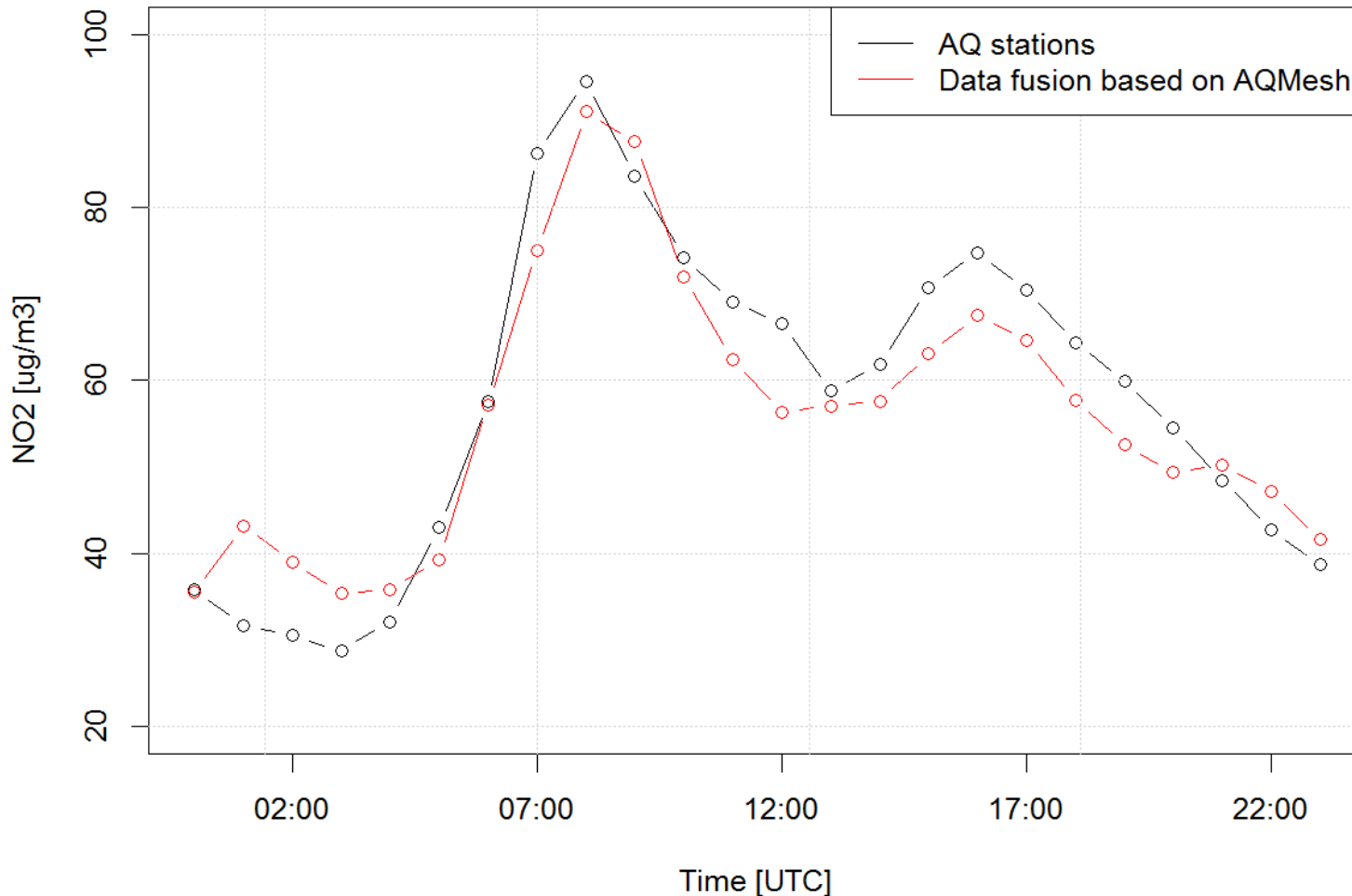


Example of 24 hours of data fusion results in Oslo, combining PM₁₀ measurements from the AQMesh units with a long-term average basemap derived from the EPISODE model, here shown for 22 March 2016.



Data fusion maps: Daily cycle of NO₂, PM₁₀, and PM_{2.5} for Oslo on January 6 2016 (NO₂) and 22 March 2016 (PM).

Comparison to AQ monitoring stations

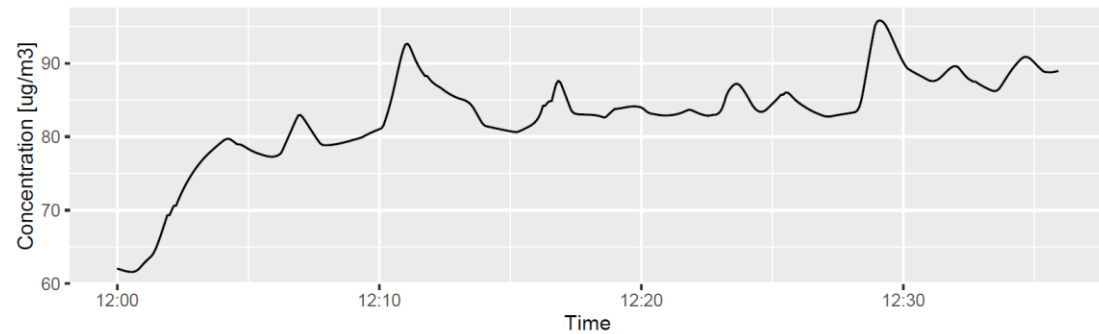
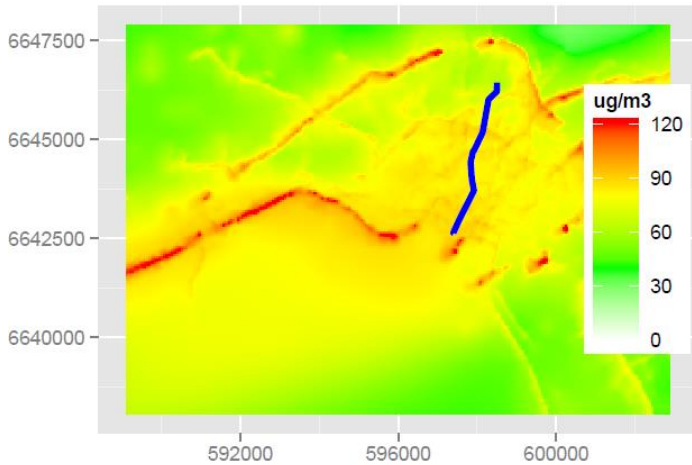


The fused maps not only replicate the patterns of the typical daily cycle, but are able to reproduce the overall magnitude in terms of actual concentrations.

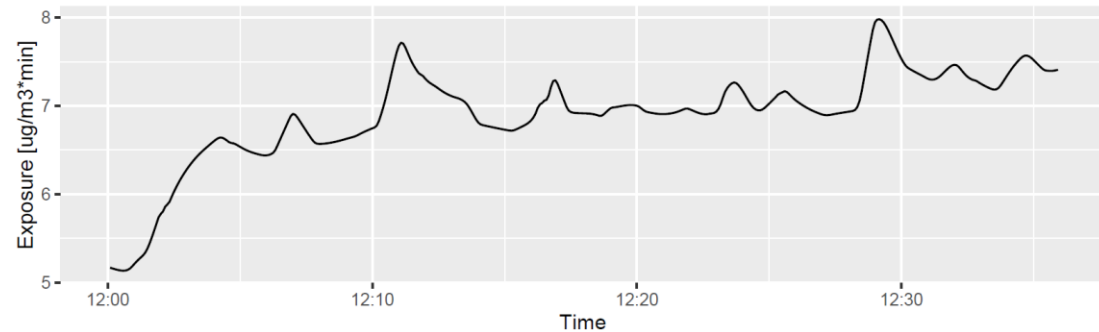
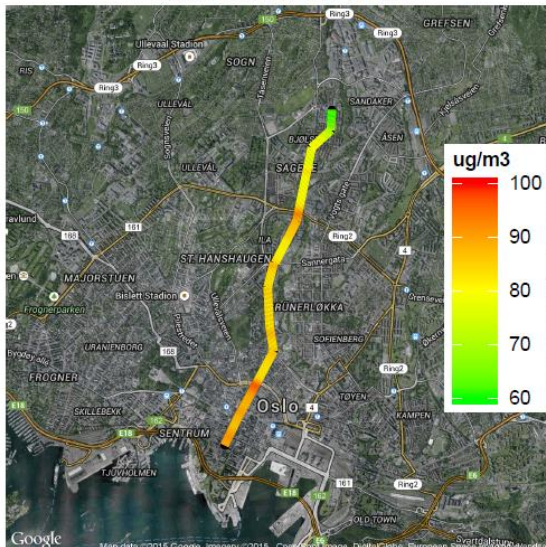
This shows that despite high uncertainty at the individual sensor level, we can tease out a useful and realistic signal from an entire network sensor nodes.

Entire daily cycle of NO₂ as measured by the reference air quality monitoring stations versus the NO₂ concentrations provided by the data fusion map.

Applications of data fusion maps

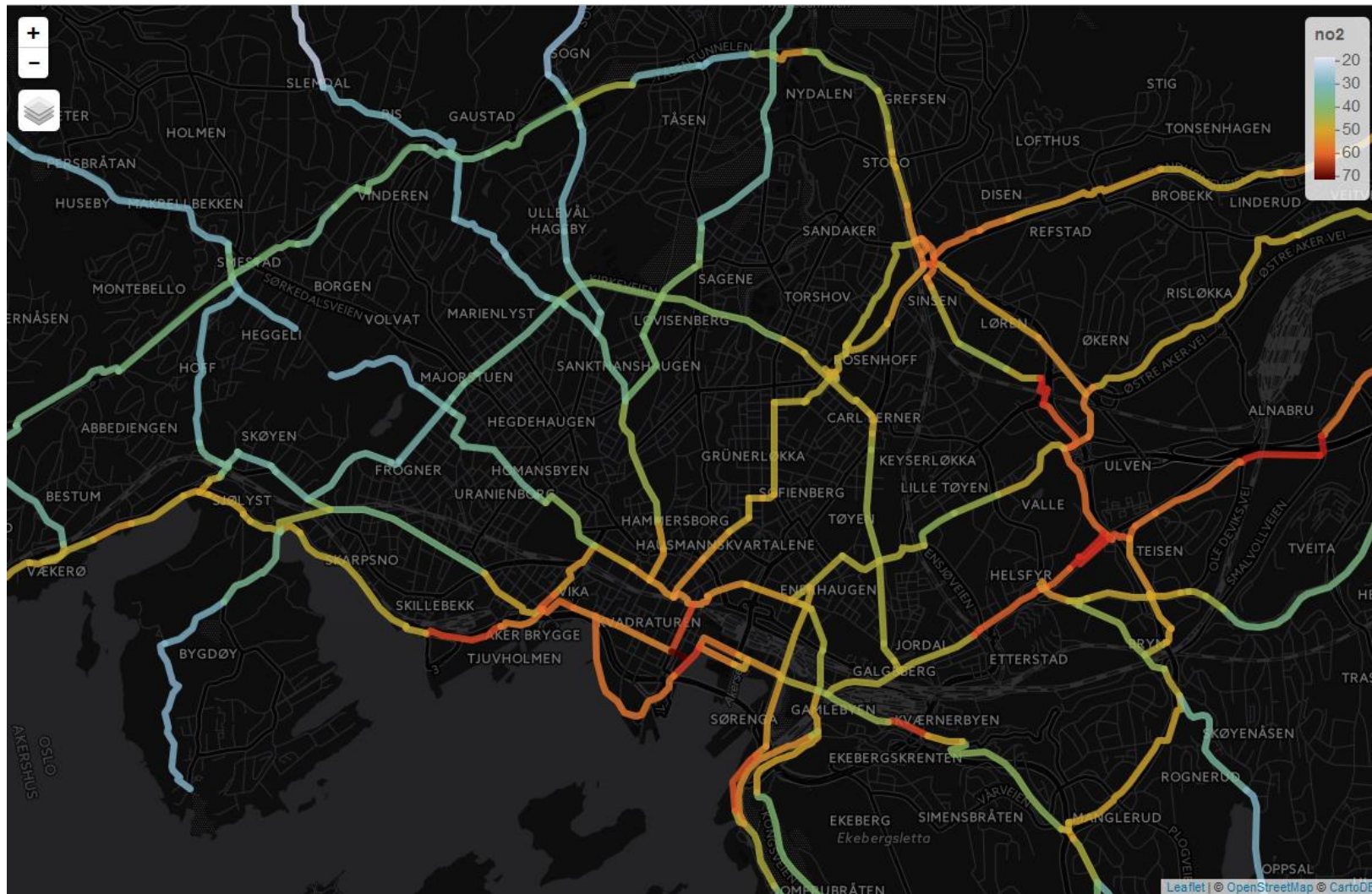


Concentrations NO2



Since the data fusion maps represent the best guess concentration field at a given time, they can be used to provide up-to-date information about personal exposure, for example along a given route through the city.

Applications of data fusion maps



Estimated real-time NO₂ concentrations along major Oslo bike paths, extracted from a data fused map.

Some lessons learned

- Automated **quality control of the data** is absolutely **crucial** (but challenging to implement in a robust fashion)
- Using **simulated data** was very **useful for algorithm development**
- The **mapping quality** is dependent on several parameters
 - Number of sensors: The number of deployed units ideally should be **greater than ~50 per city** for reasonable results
 - Also keep in mind that several data points are usually lost due to **data quality issues!**
 - Calibration **biases** in sensors are **common and problematic** (particularly when shifting over time) → **co-location with reference station** before deployment is crucial and ideally a **network-based inter-calibration system**
- The impact of bad sensor data can be compensated to some extent by larger number of nodes and thus higher density (network-based cal/val)
- Sensor **deployment strategy** for mapping purposes
 - Ensure good **coverage** of both background and traffic sites (as wide range of concentrations as possible)
 - Good to be **consistent** in terms of placement
 - Ensure a continuous **range of distances** between sensors, starting at very small distances (important for both data quality checking and semivariogram calculations)

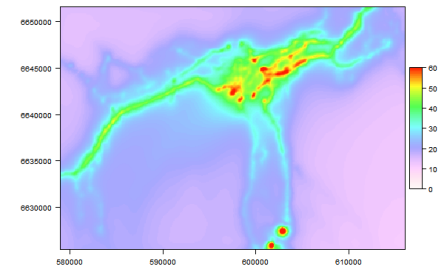
Summary

- A method was developed for creating **urban-scale air quality maps** from static crowdsourced AQ measurements
- Resulting maps reproduce the **overall spatial patterns** of AQ in the city and at the same time quantitatively **reproduce the observations**
- Quality of the resulting maps is **dependent on quality of observations** (and model)
 - Maps are sensitive to outliers -> Thorough automated quality control of observations necessary before use for mapping
 - Best results are currently achieved during strong pollution episodes (best/highest signal-to-noise ratio in sensors)
- There are **many potential applications** of real-time AQ mapping for personal exposure monitoring and custom data products for cities, but **data quality needs to improve first**
- The **feasibility** of the method could be **demonstrated** and future advances in sensor technology and deployment density will tremendously **increase its usefulness**



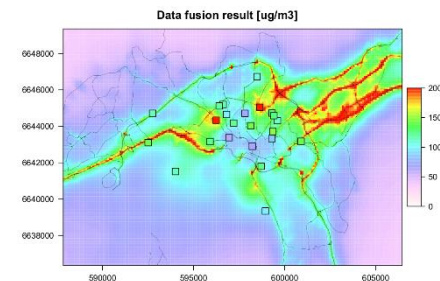
Observations

+



Model

=



Urban AQ Map

Thank you for your attention!

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