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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
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 NO₂/PM₁₀/PM₂.₅ concentration field at all locations

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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 NO\textsubscript{2} in Oslo from the EPISODE dispersion model. These kind of maps are ideally suited as a spatially distributed auxiliary dataset.
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” NO$_2$ field (in practice, unknown). Center top panel: model-derived annual average basemap of NO$_2$ 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

![Graph showing the impact of station number on root mean squared error (RMSE) in ug/m³. The graph indicates a decrease in RMSE as the number of simulated stations increases.](graph.png)
Example of the data fusion process combining crowdsourced observations with a modeled basemap, here shown for NO$_2$ on 6 January 2016 at 9:00 UTC.
Example of a data fusion-based surface concentration field of NO$_2$ for Oslo, Norway, at 100 m spatial resolution (link).
Example of a data fusion-based surface concentration field of NO$_2$ for Barcelona, Spain, at 100 m spatial resolution (link).

Example of 24 hours of data fusion results in Oslo, combining NO$_2$ measurements from the AQMesh units with a long-term average basemap derived from the EPISODE model, here shown for 6 January 2016.
Example of 24 hours of data fusion results in Oslo, combining PM$_{10}$ 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 PM$_{10}$ 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 NO$_2$, PM$_{10}$, and PM$_{2.5}$ for Oslo on January 6 2016 (NO2) and 22 March 2016 (PM).
Comparison to AQ monitoring stations

Entire daily cycle of NO$_2$ as measured by the reference air quality monitoring stations versus the NO$_2$ concentrations provided by the data fusion map.

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.
Applications of data fusion maps

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.
Thank you for your attention!

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