Maximizing insights from air quality sensor networks through continuous performance evaluation

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What I’m going to talk about

Project background

What we learned

Conclusions

Evaluating uncertainty in sensor networks for urban air pollution insights

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Project background
The Breathe London pilot project (BL)

Sensor network

Mobile monitoring

Air quality modeling

Wearables study

Additional activities

www.breathelondon.org/pilot
How reliably can a large network of sensors characterize local air pollution?
A data-rich context for validation

- Extensive network of reference-grade monitors
- ~100 sensor-reference collocations

![Map of Greater London with London reference and BL sensor markers](image1)

![BL sensor pod](image2)

![London Air Quality Network (LAQN) monitor](image3)

![Graph showing data](image4)
Ongoing sensor evaluation with “test” sensors that remained at reference sites

Unit 17 at IS2

Unit 83 at SK6

NO₂ (µg m⁻³)

I hope to convince you to install a subset of sensors alongside reference monitor(s) for the full duration of any sensor network deployment.
## Context for comparing BL and reference networks

<table>
<thead>
<tr>
<th></th>
<th>Breathe London pilot project (BL)</th>
<th>London reference</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Device</strong></td>
<td>AQMesh small sensor air quality monitoring system</td>
<td>Reference monitors from multiple UK networks: London Air Quality Network (LAQN), Air Quality England (AQE) network, and Automatic Urban and Rural Network (AURN)</td>
</tr>
<tr>
<td><strong>NO₂ method</strong></td>
<td>Electrochemical sensor</td>
<td>Chemiluminescent analyzer</td>
</tr>
<tr>
<td><strong>Total number</strong></td>
<td>100</td>
<td>105</td>
</tr>
<tr>
<td><strong>Site types</strong></td>
<td>Kerbside (n=36), Roadside (n=36), and Urban Background (n=40)</td>
<td>Kerbside (n=12), Roadside (n=62), and Urban Background (n=31)</td>
</tr>
<tr>
<td><strong>Modeled annual mean NO₂ (2019)</strong></td>
<td>36 µg m⁻³</td>
<td>41 µg m⁻³</td>
</tr>
</tbody>
</table>

Based on modeling, average NO₂ pollution at reference sites is expected to be **5 µg m⁻³ higher** than at BL sites.
NO$_2$ methodology

- QA/QC
  - Automated procedures (e.g., flag redaction and high/low limits)
  - Weekly manual inspection

- Calibration
  - Physical collocation
  - Remote network calibration

- Ozone cross-interference correction

- Uncertainty evaluation
  - Average hourly uncertainty (RMSE) of ± 35% compared to reference measurements

See detailed methods in our paper and in the BL QA/QC Procedures document.
What we learned
Long-term network trends

![Graph showing NO₂ concentrations and their differences over time in London and a reference location.](image-url)
Long-term network trends

![Graph showing long-term network trends in NO₂ (µg m⁻³) and difference (µg m⁻³) over time. The graph compares Breathe London with a reference using distinct line styles and shaded areas to indicate specific time periods. The x-axis represents months from Oct 2018 to Oct 2020, while the y-axis shows NO₂ concentrations and differences.]
Long-term network trends
Weekday diurnal patterns at near-road and urban background sites
Weekday diurnal patterns at near-road and urban background sites
Local hotspots

BL sensor pod

![Graph showing NO₂ concentration over time]

- **NO₂ (μg m⁻³)**
- **Hour (LT)**
- **BL Network**
- **Holloway Bus Garage**
Can we rely on these numbers?

Sensor failure
Cross-interference
Bias
Drifting baselines

Guess I’ll have to look at my “test” sensors to find out

“The sensor situation” part 2
"Test" sensors as indicators for sensor network performance

Bias and error of "test" sensors varied seasonally and peaked during the summer.
Case study 1: Interpreting a short-term episode with elevated NO2 sensor measurements (July 2019)

Network mean concentrations

\[ R^2 = 0.69 \]

Is a real pollution event causing elevated BL network measurements?

Are the “test” sensors performing well?

“Test” sensor measurements are much higher than collocated reference

We can infer that the BL network spike was caused by sensor error

“Test” sensor timeseries compared to collocated reference monitor
Case study 2: Interpreting a short-term episode with elevated NO2 sensor measurements (December 2019)

Network mean concentrations

"Test" sensor timeseries compared to collocated reference monitor

Is a real pollution event causing elevated BL network measurements?

Are the “test” sensors performing well?

“Test” sensor measurements closely track collocated reference

We can infer that BL network spike was really caused by elevated pollution levels
Conclusions
Differentiating robust air pollution patterns from measurement artifacts

- The BL network effectively characterized NO$_2$ pollution patterns, with some irregularities
  - We validated sensor network results using comparisons to London’s reference network
- In a place without an extensive reference network, you are left without the dashed line to compare against
  - How do you tell if measured events (like the ones below) are real?
Differentiating robust air pollution patterns from measurement artifacts

- We demonstrated the use of representative “test” sensors that were continuously stationed at reference sites as an indicator for network performance.
- Projects should use at least one reference monitor or another source of reliable measurements to track sensor performance on an ongoing basis.
In the future?

“The sensor situation” part 3

Using sensors is so much easier now that technology, calibration, and QA/QC has improved, and my sensors meet certain performance standards.
Thanks for listening!

Contact

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EDF’s Global Clean Air team
Extra slides
Case study 3: Correction for seasonal sensor bias

Bias (and RMSE) of “test” sensors varies seasonally, peaks during the summer

Application of monthly bias correction derived from “test” sensor collocations corrects irregularities in network mean timeseries
Comparison of modeled and measured NO2 at individual monitoring sites
Diurnal (hour-of-day) and day-of-week network patterns
Sensor bias vs. temperature during “test” collocations