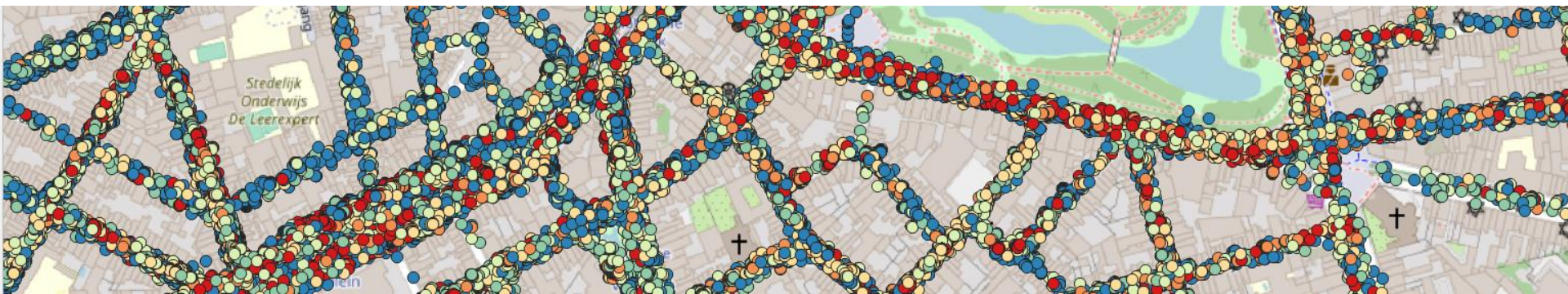


Opportunistic Mobile Air Quality Mapping Using Service Fleet Vehicles: *from point clouds to actionable insights*

Air Sensor International Conference 2022

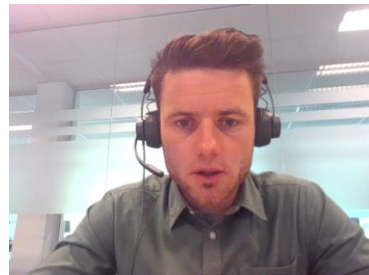


Jelle Hofman^{1,2}, Valerio Panzica La Manna², Edurne Ibarrola³, Miguel Escribano Hierro³, Martine Van Poppel¹

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³ Kunak Technologies SL, Pamplona, Spain



GOAL



- **AIM:** “Collection of real-time fine-grained air quality data to gain more insight in urban air pollution exposure”
- **Solution:** Kunak Air Mobile (<https://www.kunak.es/en/>)
 - Alphasense : NO₂, O₃ & PM
 - LTE-M
 - GPS
 - Dedicated housing: Laminar flow/avoid turbulence
- **Deployment** 20 sensors in Antwerp (Belgium)
 - Postal service: “at every doorstep”
 - 6V power supply via wiring vans
 - Monitoring resolution day (10 sec) + night (5 min)
- **Study:**
 - Co-location calibration & validation: Jan-Feb, 2021
 - Data collection: March-Sept, 2021
 - <https://www.imeccityofthings.be/en/projecten/bel-air>

kunak[®]
SENSING ANYWHERE



**CITY
OF
THINGS**

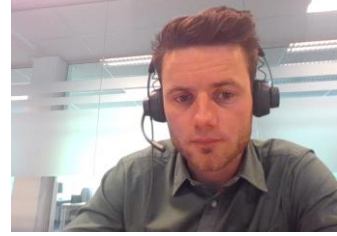
imec



CALIBRATION & VALIDATION



SENSOR CALIBRATION & VALIDATION



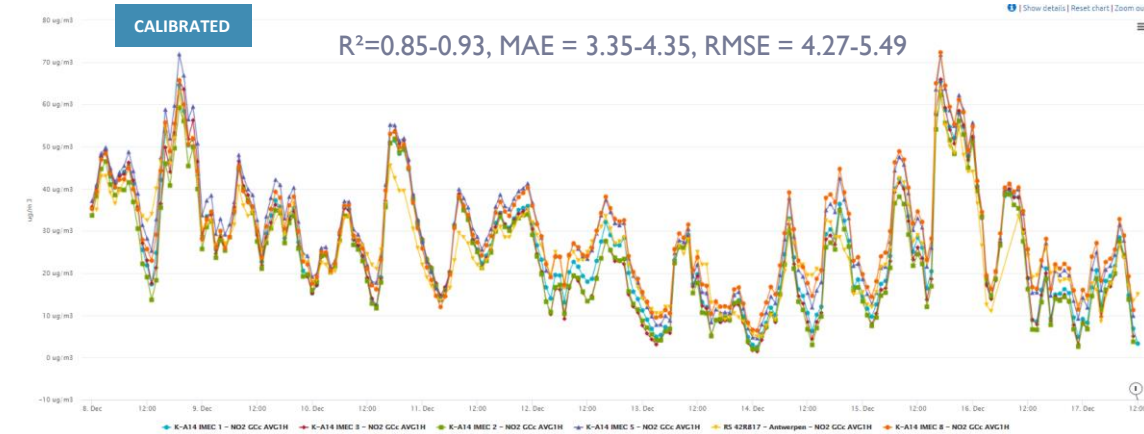
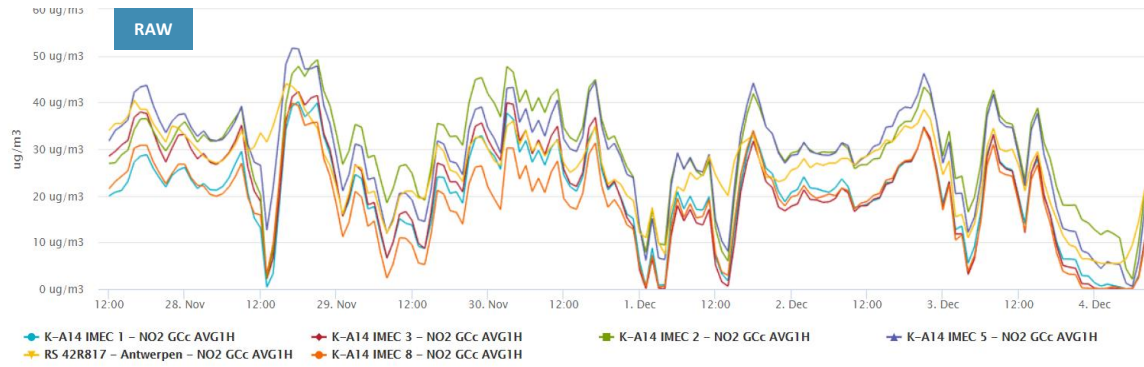
- Device property algorithm
 - Compensation temp/RH
 - Cross-sensitivity NO₂-O₃
 - mV → ppb or µg/m³ conversion
- Local calibration
 - PM composition/environmental conditions
 - Co-location AQMS
 - Baseline/span calibration NO₂
 - Mass factor (slope) correction PM
- All sensor co-located at AQMS (R817, VMM)
 - 3 in fixed shields
 - 17 in mobile enclosure



LOCAL CALIBRATION



- Calibration in 4 batches of 5 sensors
 - Within fixed shields
 - 1 week: calibration (training)
 - 1 week validation
- Overall good performance for NO₂
 - Accuracy
 - **Precision**
 - Supplementary/Class 1 (<25%) at hourly level
- Moderate performance PM
 - Supplementary/Class 1 (<50%) at daily level

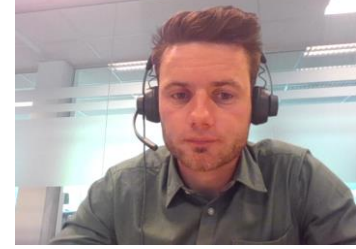


	Average Performance				
	NO2	PM1	PM2.5	PM10	
Mean REF	25.88	12.27	13.47	18.41	
Mean sensor	21.11	5.01	11.11	16.33	
R ²	0.88	0.85	0.64	0.57	
MAE	3.62	4.82	5.20	8.82	
RMSE	4.42	6.37	7.16	11.33	
Wcm	24.99	90.09	130.44	175.64	EU Equivalence Tool v3.1
Wcm	14.57	74.63	79.23	-	VMM

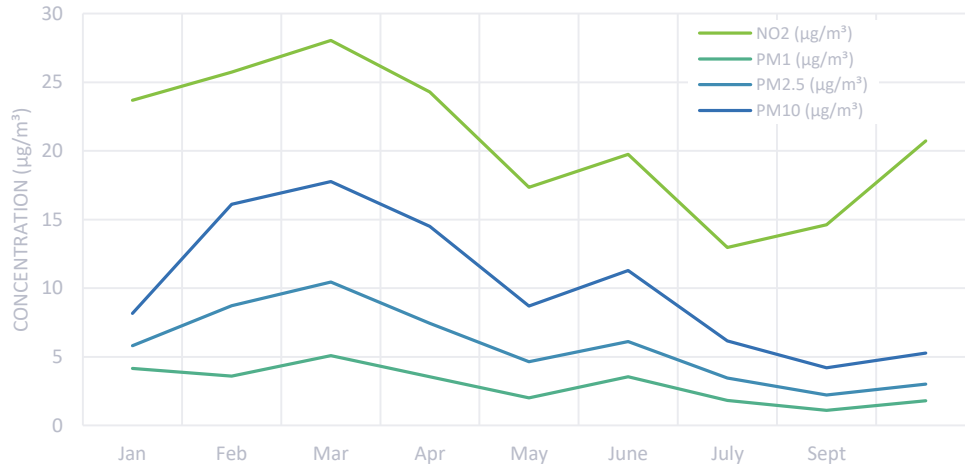
MOBILE DEPLOYMENT



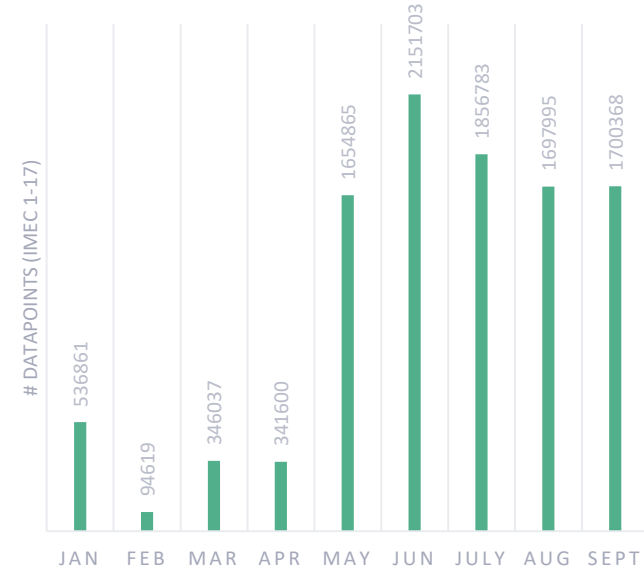
SENSOR DEPLOYMENT



- All sensor batches deployed between Jan and March.
 - 17 deployed on vans
 - 3 remained co-located with R817 (validation)
- Opportunistic data collection: March - Sept 2021
- Temporal monitoring coverage (Jan-Sept)

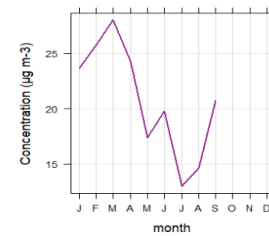
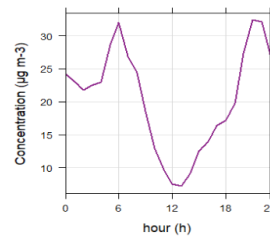
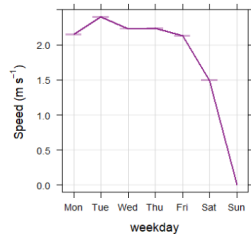
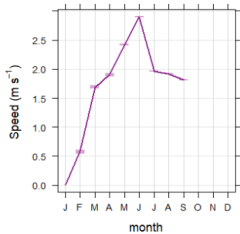
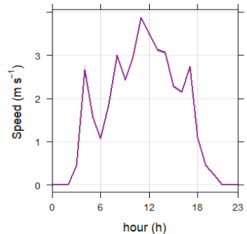
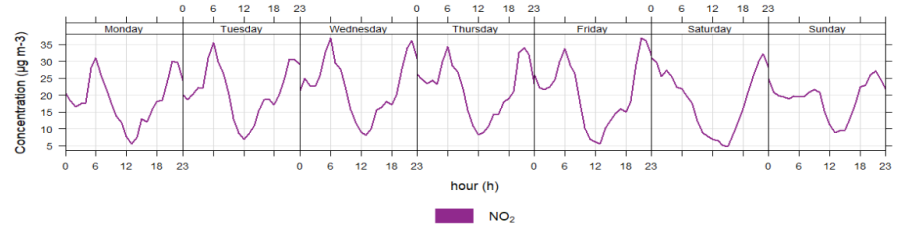
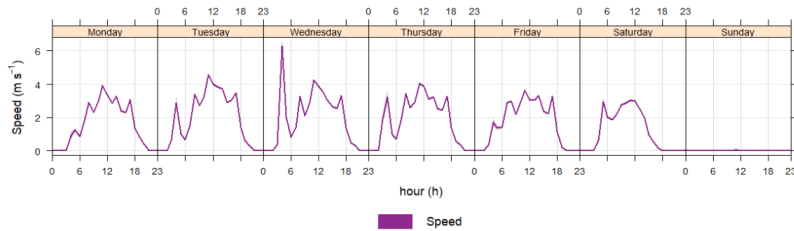
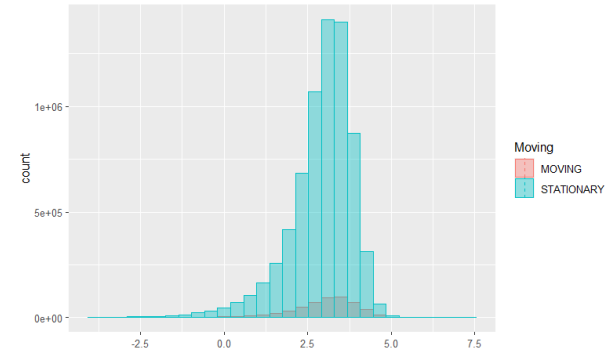
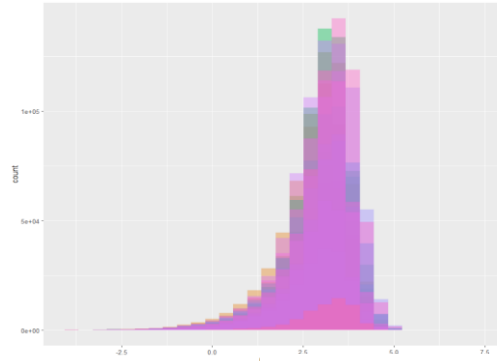


DATA COVERAGE (N=10380831)



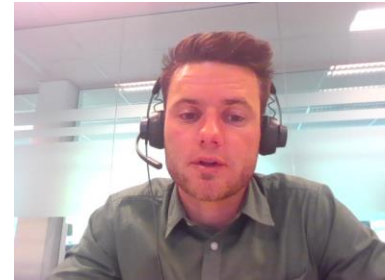
SENSOR DATA

- $\text{NO}_2 \sim$ SENSORS
- $\text{NO}_2 \sim$ SPEED
- Operation time:
 - 92.7% stationary (speed=0)
 - 7.3% moving (speed > 0)



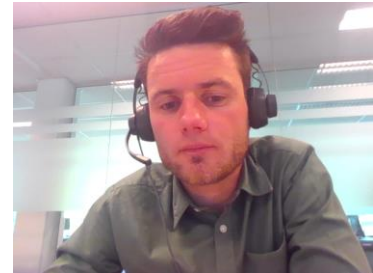
mean and 95% confidence interval in mean

mean and 95% confidence interval in mean

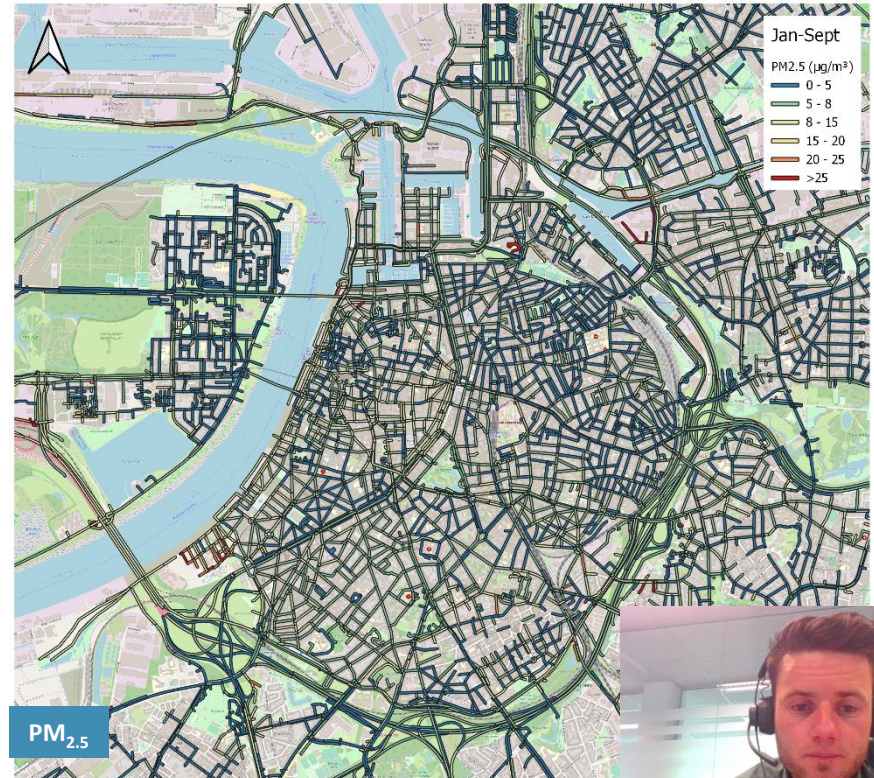
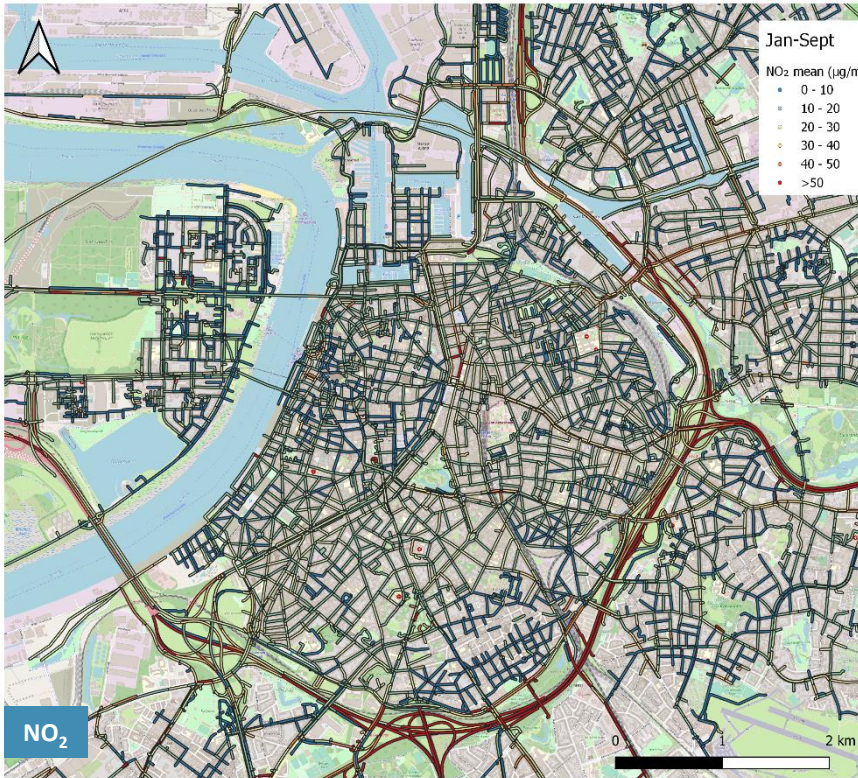


SPATIAL AGGREGATION

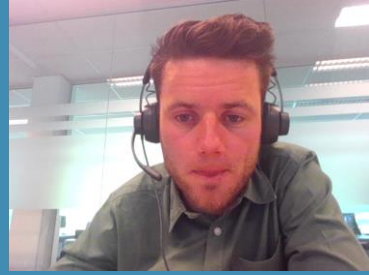
- Spatial aggregation datapoints into street segment buffers (10m radius)
 - Count/Min/25%/Mean/Median/75%/Max



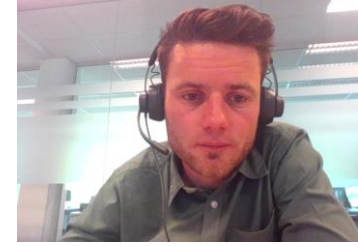
POLLUTANTS



REPRESENTATIVITY



SPATIOTEMPORAL REPRESENTATIVITY



- 10 sec measurements in both space & time: representative?

- Solutions:

- Subsampling analysis to determine required coverage threshold

Van den Bossche et al. 2016 <https://lib.ugent.be/catalog/rug01:002300079>

Apte et al. 2017 <https://pubs.acs.org/doi/10.1021/acs.est.7b00891>

Chen et al. 2022 <https://doi.org/10.1016/j.atmosenv.2022.118936>

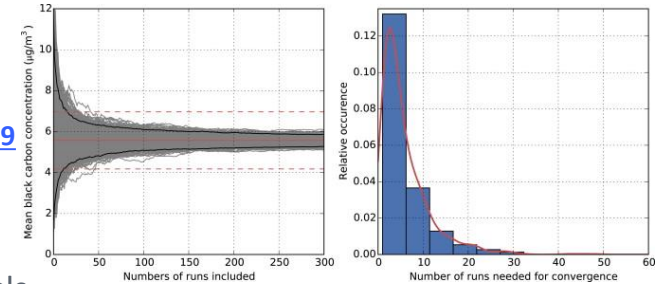
- Air Quality Inference in space-time based on machine learning models

Do et al. 2020 <https://doi.org/10.1109/JIOT.2020.2999446>

Xuening et al. 2021 <https://doi.org/10.1145/3461353.3461370>

Paliwal et al 2021 <https://www.youtube.com/watch?v=9yjaScDqINE>

Hofman et al. 2022 <https://doi.org/10.1016/j.envsoft.2022.105306>



Environmental Modelling and Software 149 (2022) 105306



Spatiotemporal air quality inference of low-cost sensor data: Evidence from multiple sensor testbeds

Jelle Hofman^{a,b,*}, Tien Huu Do^{c,e}, Xuening Qin^{d,e}, Esther Rodrigo Bonet^{c,e}, Wilfried Philips^{d,e}, Nikos Deligiannis^{c,e}, Valerio Panzica La Manna^a

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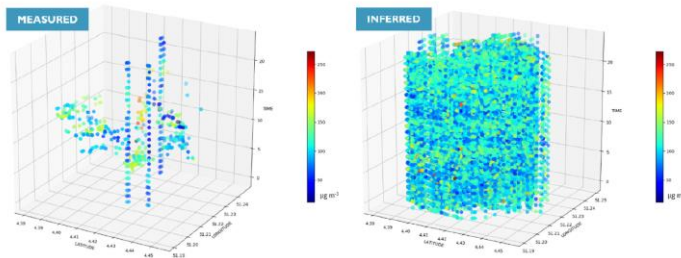
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ARTICLE INFO

ABSTRACT

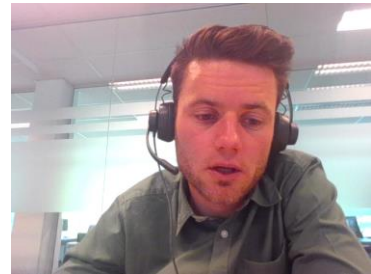


CONCLUSIONS



CONCLUSIONS

- Mobile AQ sensors are able to generate **actionable results**
- Proper **calibration & validation** is needed to determine their potential & quantify associated uncertainty for each pollutant (interpretation)
 - NO₂>PM, impact housing
- **Data Aggregation** Tools: point clouds → AQ maps
- **Comprehensive** AQ maps:
 - Coverage thresholds/subsampling analysis
 - AQ inference models



THANKS!



QUESTIONS?

