EPFL

Disal

Signals, Instruments, and Systems – W12

Environmental Sensing Systems – Mobile Sensor Networks

Outline

- Mobile sensor networks
  – Motivation
  – Some pioneering examples

- Air quality monitoring
  – Motivation and challenges
  – The OpenSense project
    - Modeling approaches
    - System design
    - Mobility effects and handling
    - Mapping

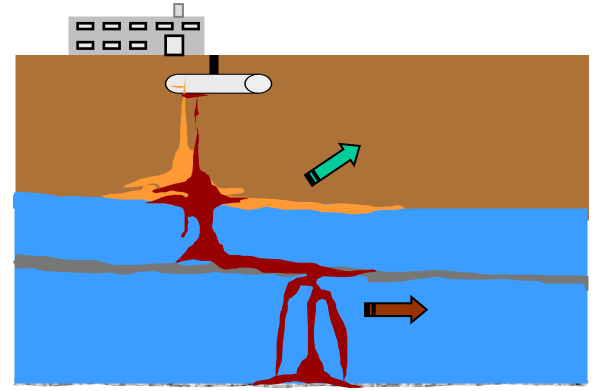
Motivation

Motivation

Seismic Structure response

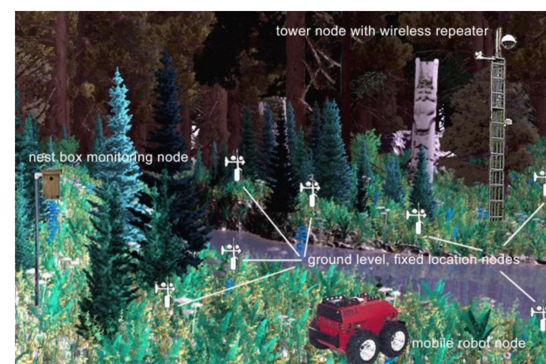
Marine Microorganisms

- Micro-sensors, on-board processing, and wireless interfaces all feasible at very small scale
  - can monitor phenomena "up close"
- Will enable spatially and temporally dense environmental monitoring
- Will enable precise, real-time alarm triggering
- Embedded networked sensing will reveal previously unobservable phenomena



Contaminant Transport

Ecosystems, Biocomplexity

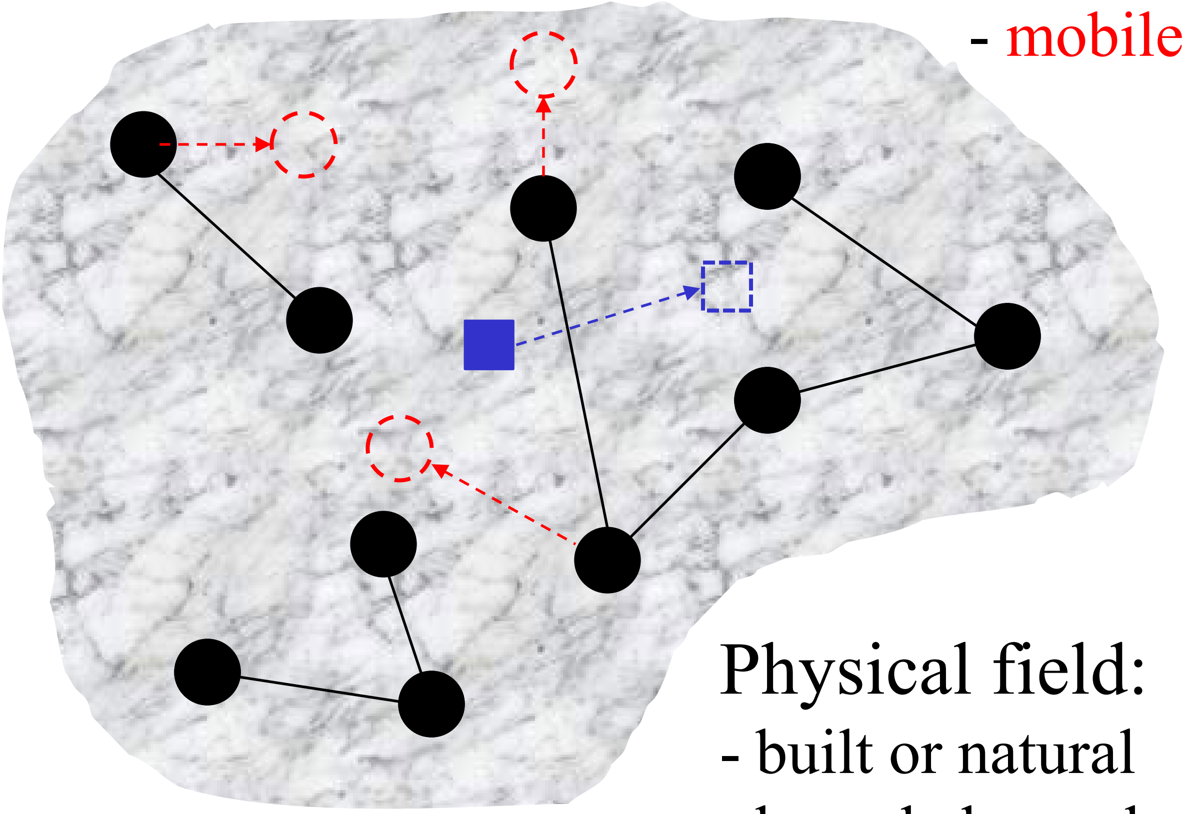


Adapted from D. Estrin, UCLA

Environmental Monitoring

Typical solution in environmental monitoring:
- sparse sensing
- expensive station(s)
- field estimation via physics- or chemistry-based models
- possible mobility

Distributed solution for augmentation:
- size, cost
- number
- networked
- mobile



Physical field:
- built or natural
- bounded or unbounded
- 2D or 3D

Motivation for Mobile Sensor Networks

For monitoring events and processes that have a large spatial and temporal distribution, require in-situ measurements, and that generate data which need to be available in real-time, mobile sensor networks can:

- Leverage mobility of available physical motion vectors (parasitic mobility, uncontrolled by the sensing system)
- Extend the sensing coverage with the same number of sensing assets
- Facilitate deployment, gathering, and maintenance operations

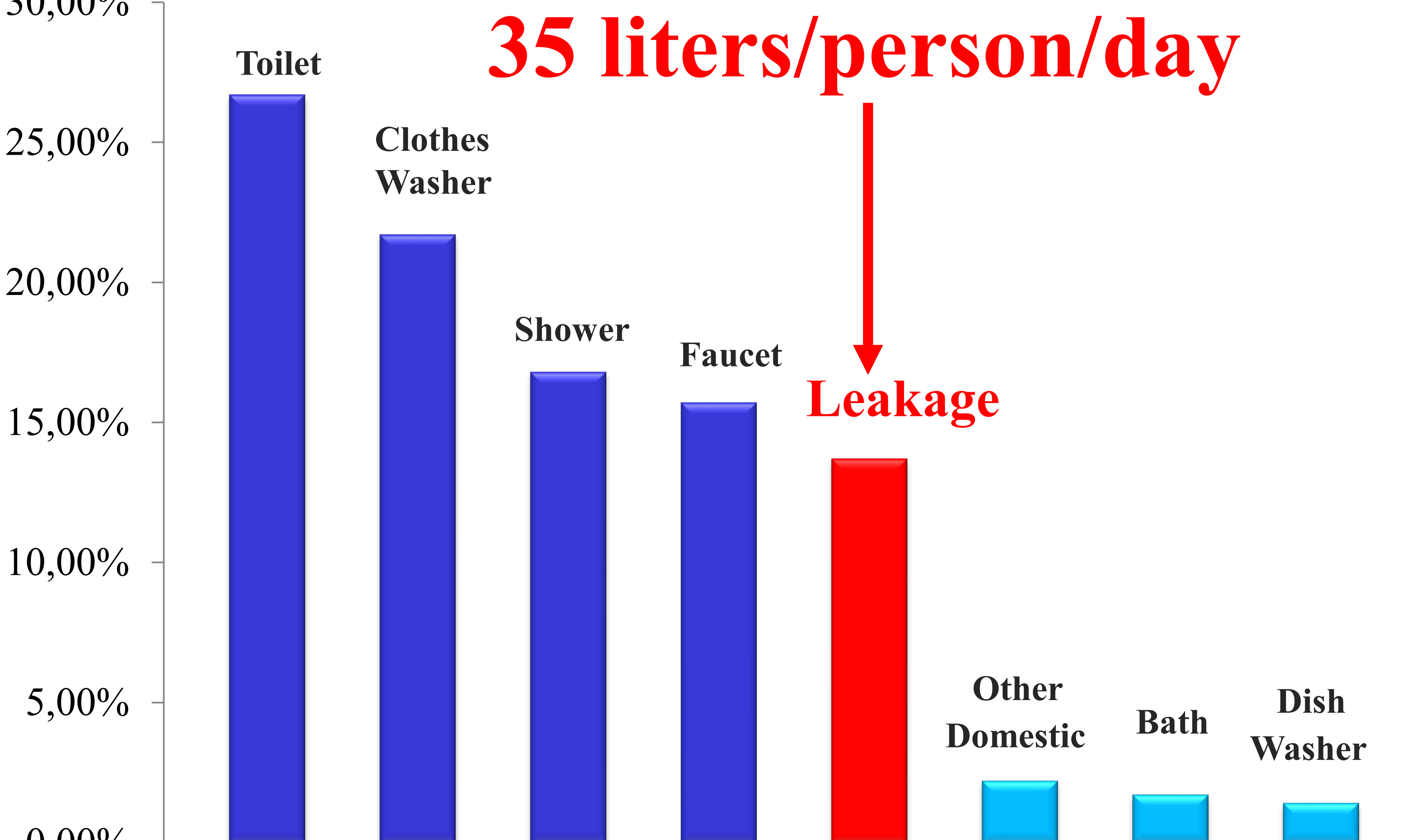
A Pioneering Example of Mobile Sensor Network

PipeProbe: A Mobile Sensor Droplet for Mapping Hidden Pipeline

Tsung-te (Ted) Lai
Yu-han (Tiffany) Chen
Polly Huang
Hao-hua Chu

National Taiwan University

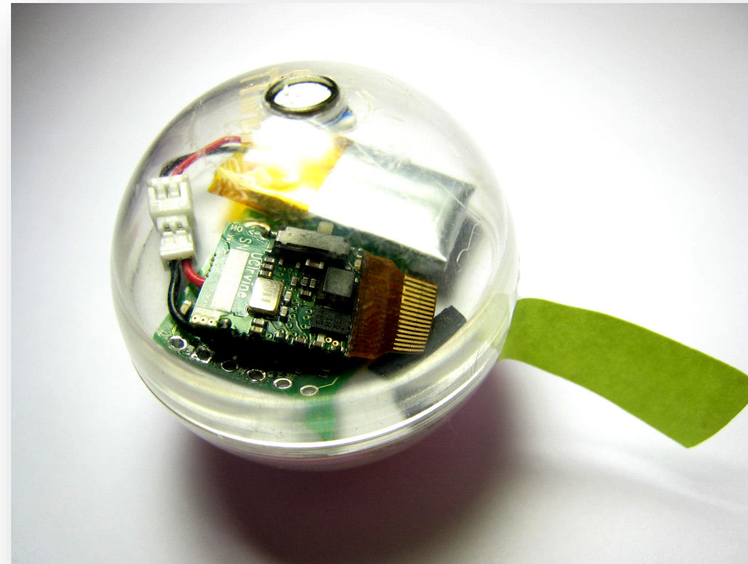
Residential Water Usage



Source: Residential End Uses of Water, AWWA Research Foundation

PipeProbe System

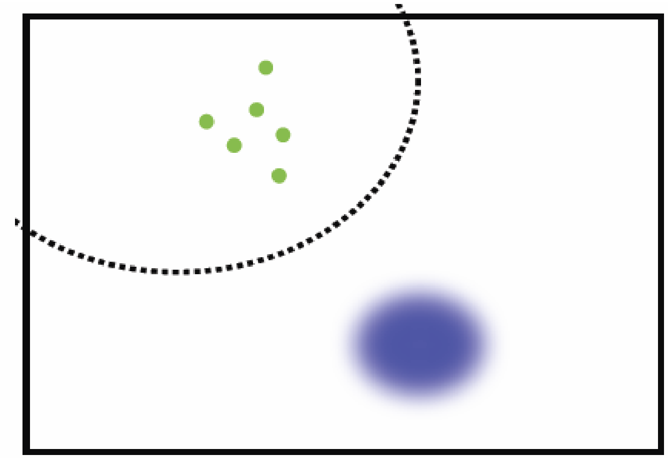
- Map 3D spatial topology of water pipelines
- Leverage natural water flow for mobility
- 13mm(L) x 11mm(W) x 7mm(H), 3 grams
- IT basis: ECo wireless sensor mote (Pai Chou, UC Irvine)
- Com: radio
- Sensors: pressure, 3-axis accelerometer, gyroscope



[Lai et al., *ACM Trans. Sensor Networks*, 2013]

Another Pioneering Example: Virtual Fencing for Cattle

- Dynamically adjust regions where cows can graze
- Improve land management
- Reduce cost of fence installation and maintenance
- Real-time health monitoring
- Remote management
- Detailed histories of motions and actions



[Schwager et al., *Journal of Field Robotics*, 2008]

Air Quality Monitoring

Importance of Air Quality

On March 25, 2014, the WHO reported:

"… **in 2012 around 7 million people died** – one in eight of total deaths – as a result air pollution exposure. This finding more than **doubles previous estimates** and confirms that air pollution is now the **world's largest single environmental health risk**. "

"The new estimates are not only based on more knowledge about the diseases caused by air pollution, but also upon better assessment of human exposure to air pollutants **through the use of improved measurements and technology**."

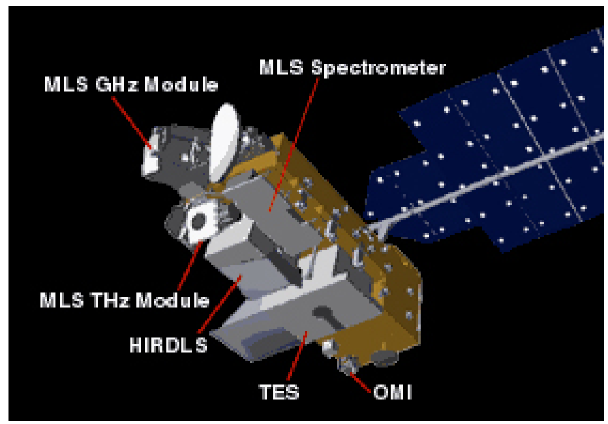
Latest data and news:
https://www.who.int/news-room/fact-sheets/detail/ambient-(outdoor)-air-quality-and-health

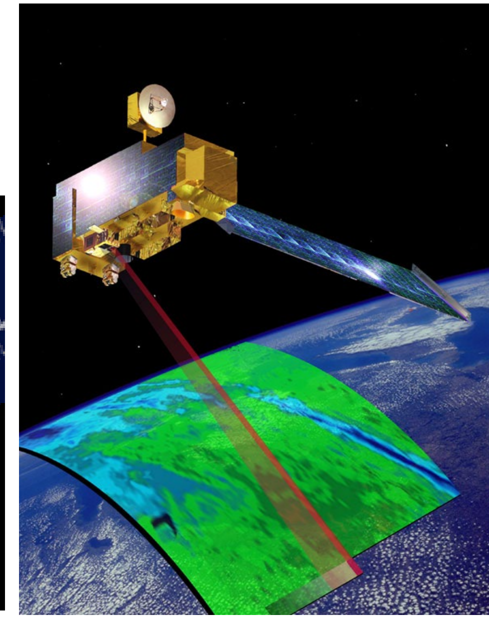
Monitoring Today

Satellite-based remote sensing

Examples:

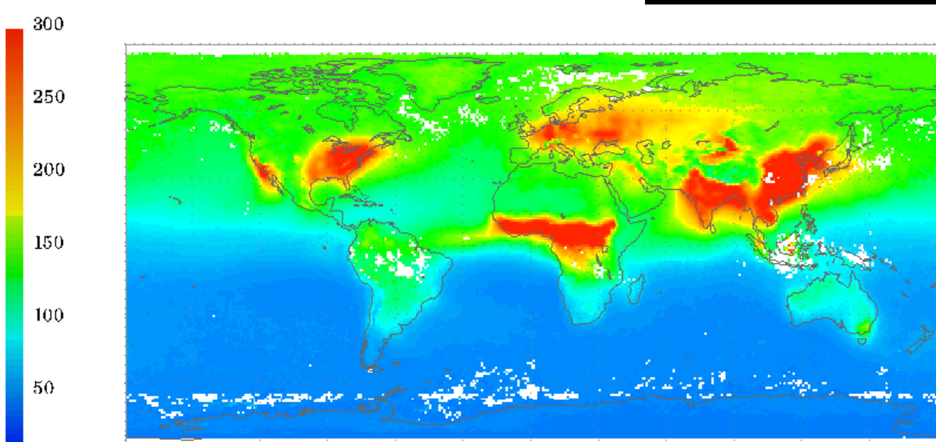
- Measurements of Pollution in the Troposphere (MOPITT on Terra satellite)
- Ozone Measurement Instrument (OMI on Aura satellite)



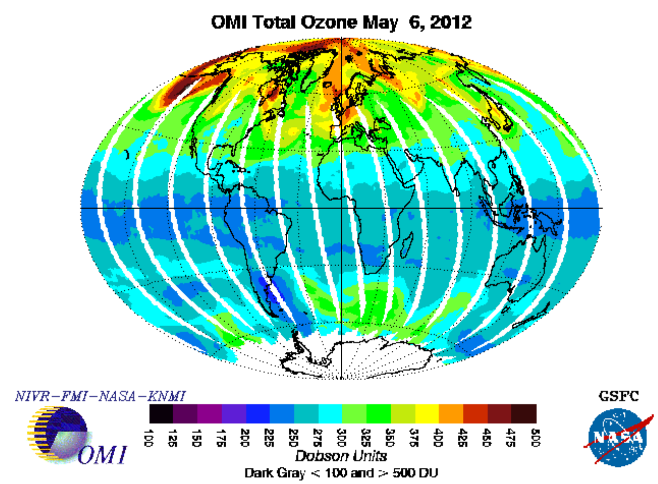


Features:

- daily scans
- large coverage
- homogeneous quality
- sensitive to cloud coverage
- low resolution



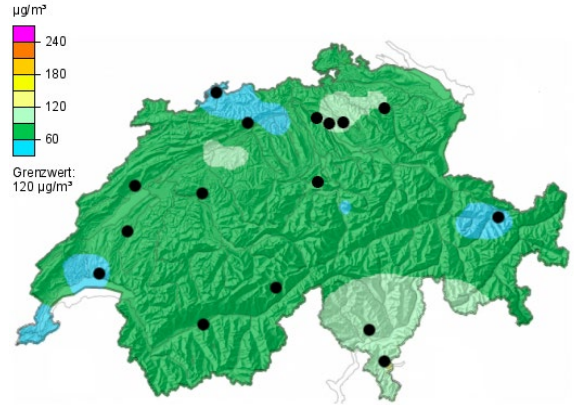
MOPITT CO Mixing Ratio at Surface (ppbv)



EPFL

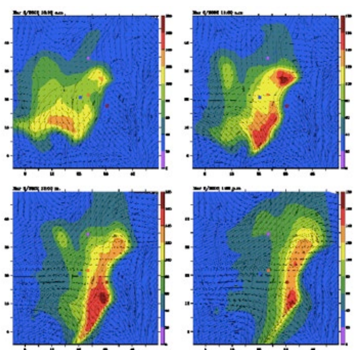
Monitoring Today

Stationary and expensive stations



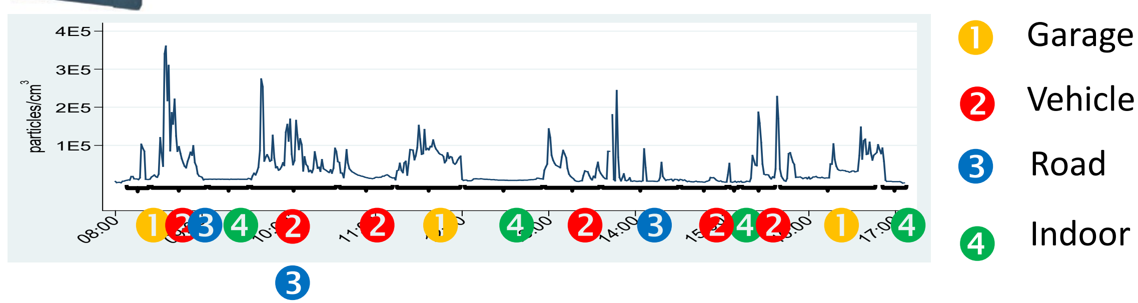
Sparse sensor network (Nabel)

Expensive mobile high fidelity equipment



Coarse models (mesoscale = 1km²)

Personal exposure with specialized punctual studies



Explorative Efforts in Dense Sensing

➢ Examples of private sector initiatives

AirQualityEgg by Wicked Device;

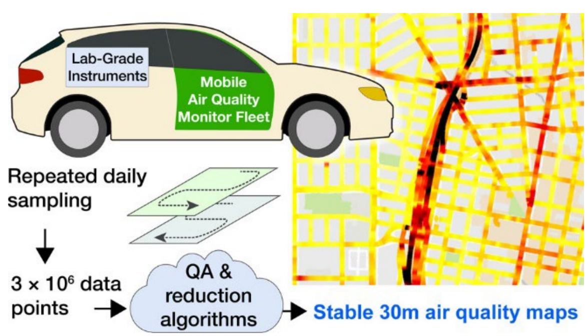
Laser Egg by Kai Terra;

Clarity Nodes by Clarity;

Airlib by Rimalu Technologies

➢ Examples of research initiatives

[Apte et al., *Environ. Sci. Technol., 2017]*

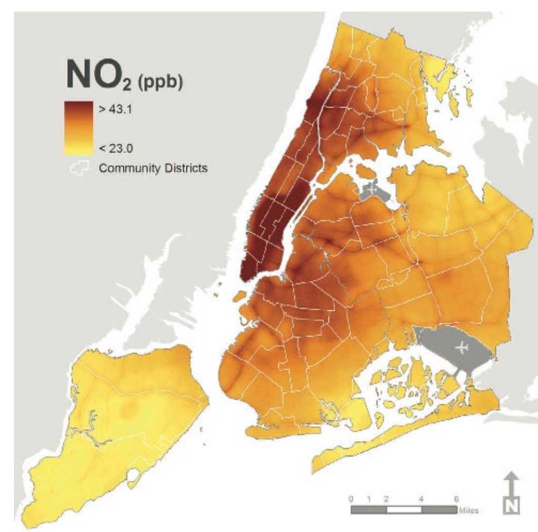


➢ Examples of city initiatives

Massive deployment of stations (150) at street-level (2008/2009 New York City Community Air Quality Survey);

Bloomberg Philanthropies with city of Paris: 150 Clarity nodes (PM 2.5/NO2) around schools with involvement of AirParif (2019)

Breathe London: 100 stationary nodes, two Google Street View cars, wearable sensors for chidren (2019)

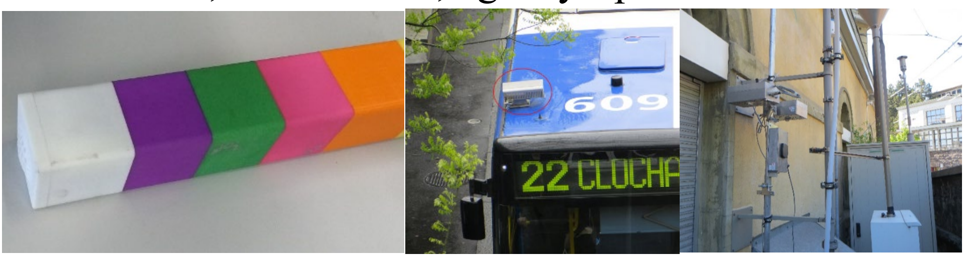


The OpenSense Project

OpenSense Vision

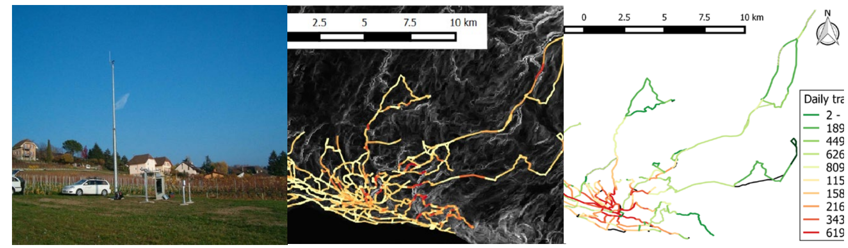
Measurement data

Citizen-, consortium-, agency-operated sensors



Explanatory variables

Land-use, meteorology, traffic



Exposure information

Personal reccomendations, health studies, urban planning, crowdsensing

High-resolution pollution maps

Process-based and data-driven statistical modeling methods

EPFL

Disal

Deployments and Approaches

		Deployments	
		Lausanne	Zurich
Mapping Approach	Process-based	EMPA	EMPA
	Data-driven	EPFL	ETH zürich

High-Resolution Maps:
Process-Based Modeling Techniques

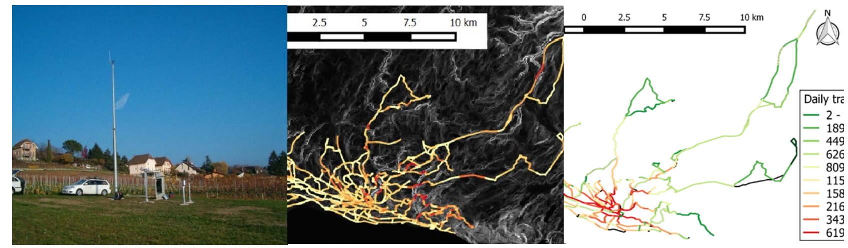
Process-Based Modeling

Measurement data

Agency-operated, high-end stations

Explanatory variables

Land-use, meteorology, traffic



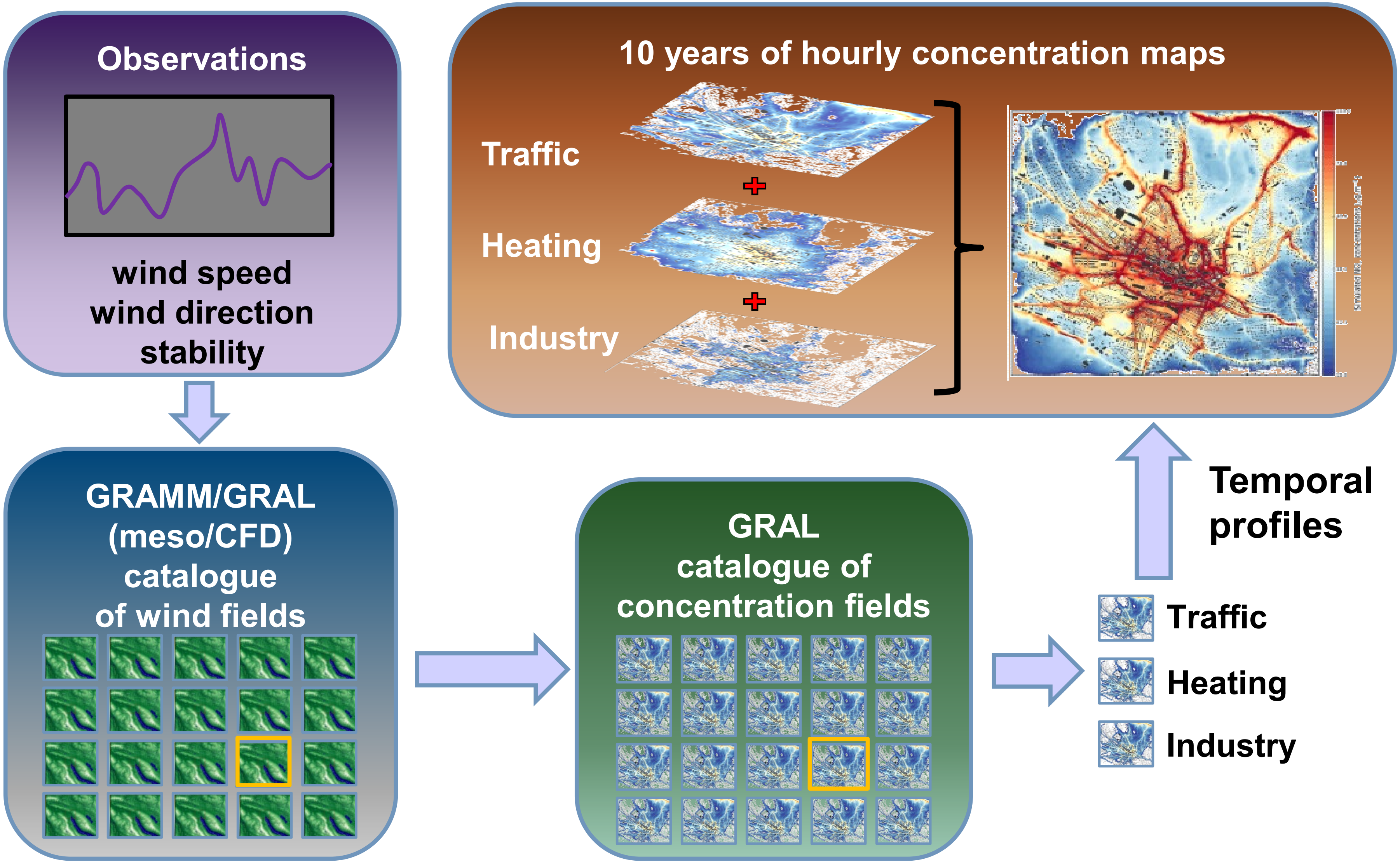
Exposure information

Personal reccomendations, health studies, urban planning

High-resolution pollution maps

Process-based modeling methods

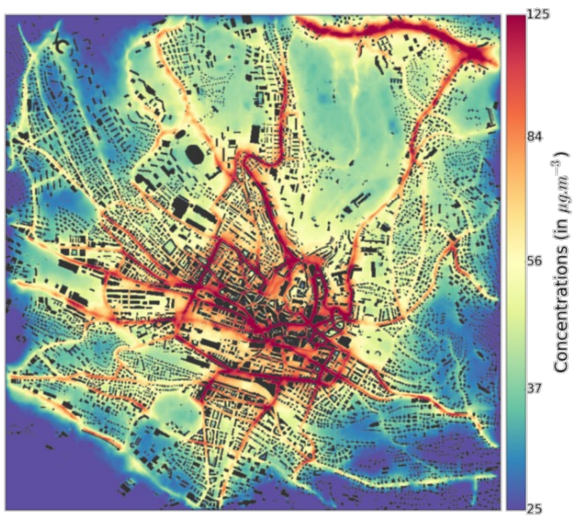
The GRAMM/GRAL Modeling Framework



[Berchet et al., *Atmospheric Environment*, 2017]

Multi-year Simulations of NO_x and PM10

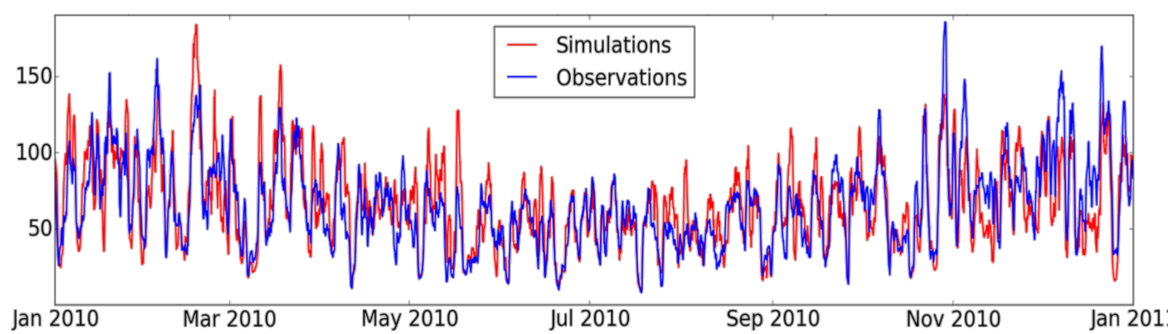
Lausanne, annual mean NO_x



- 5 m resolution, hourly output, 0-30 m above ground level
- Lausanne: ten years, 10 emission categories
- Evaluation with in situ measurements:
  - Bias < 25%
  - Correlation > 0.7 for hourly concentrations
  - Correlation > 0.8 for daily averages

EMPA

Comparison with monthly NABEL NO_x measurements in Lausanne



Correlating Health Data (Inflammatory Markers) with Environment Data (PM10)

Health data

Colaus

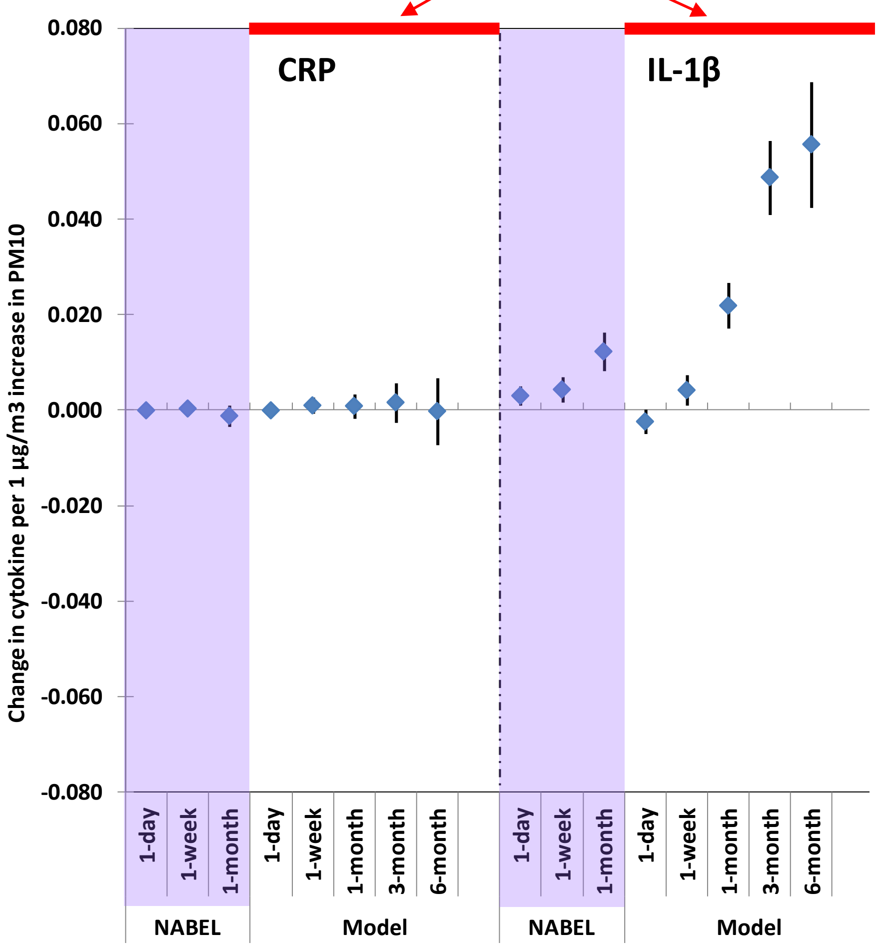
(N=6184, 2003-2012)

Link data by GIS

Exposure data

Air pollution maps from OpenSense

GRAMM/GRAL model



Association of different exposure durations with inflammatory markers by **linear models**

[Tsai et al., *Journal of Hypertension*, 2015]

Process-Based Modeling

- Strengths:
  - Well-established, can be extended with a chemistry module
  - Cost-effective (only standard IT infrastructure on top of existing measurement stations)
  - Natively designed for 3D field estimation
  - Can cheaply deliver predictions in arbitrary time windows (including retroactively if input data are available)
- Weaknesses:
  - Advanced modeling framework such as GRAMM/GRAL designed for annual average predictions
  - Estimations instead of measurements
  - Dependency on the existence and accuracy of an emission catalog
  - Cannot capture real-time field changes due to peculiar events (e.g., emergency situations, event in the city, traffic re-routing)
  - Less agile evolution in terms of sensing technology/modalities

High-Resolution Maps:

Dense Measurements Augmented with Statistical Modeling Techniques

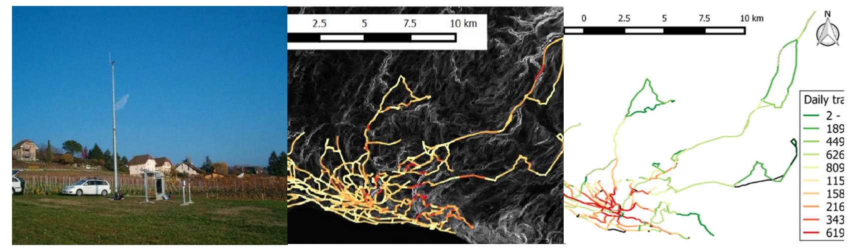
Data-Driven Statistical Modeling

Measurement data

Citizen-, consortium-, agency-operated sensors

Explanatory variables

Land-use, meteorology, traffic



Exposure information

Personal recommendations, health studies, urban planning, crowdsensing

High-resolution pollution maps

Data-driven statistical modeling methods

OpenSense Sensing Platform (Lausanne Deployment)

- Mission: measure **gas-phase pollutants** (CO, NO_2, O_3, CO_2), **particulate matter** (PM), temperature and humidity

- Gases:
  - mix of small, relatively **low cost**, electrochemical, metal oxide, and optical sensors.
  - **slow response and recovering time; need re-calibration; cross-sensitive (low selectivity)**

- Particles:
  - physical metrics: Lung-Deposited Surface Area (LDSA)
  - **nanoscale sensitivity** (<100 nanometers)
  - **high cost**

- **Mobility energy**: leverage public transportation vehicles!
- **Connectivity**: leverage GPRS since no significant energy limitations!

Overview

Enable high spatio-temporal resolution monitoring of urban air quality through mobile wireless sensor networks.

System Design → Mobility → Calibration → Mapping

System Design
- Modular & flexible
- Using low-cost sensors

Mobility
- Slow sensor response
- Mitigation approaches

Calibration
- Novel model-based & mobility-aware approaches

Mapping
- Novel statistical techniques
- Heterogeneous data sources

[Arfire, EPFL PhD thesis, 2016]

System Design → Mobility → Calibration → Mapping

Contributors: Adrian Arfire, Emmanuel Droz, Alexander Bahr, Julien Eberle (LSIR-EPFL), Ali Marjovi, Christophe Paccolat

Sensor Node Design

Data logging & Communication

Localization

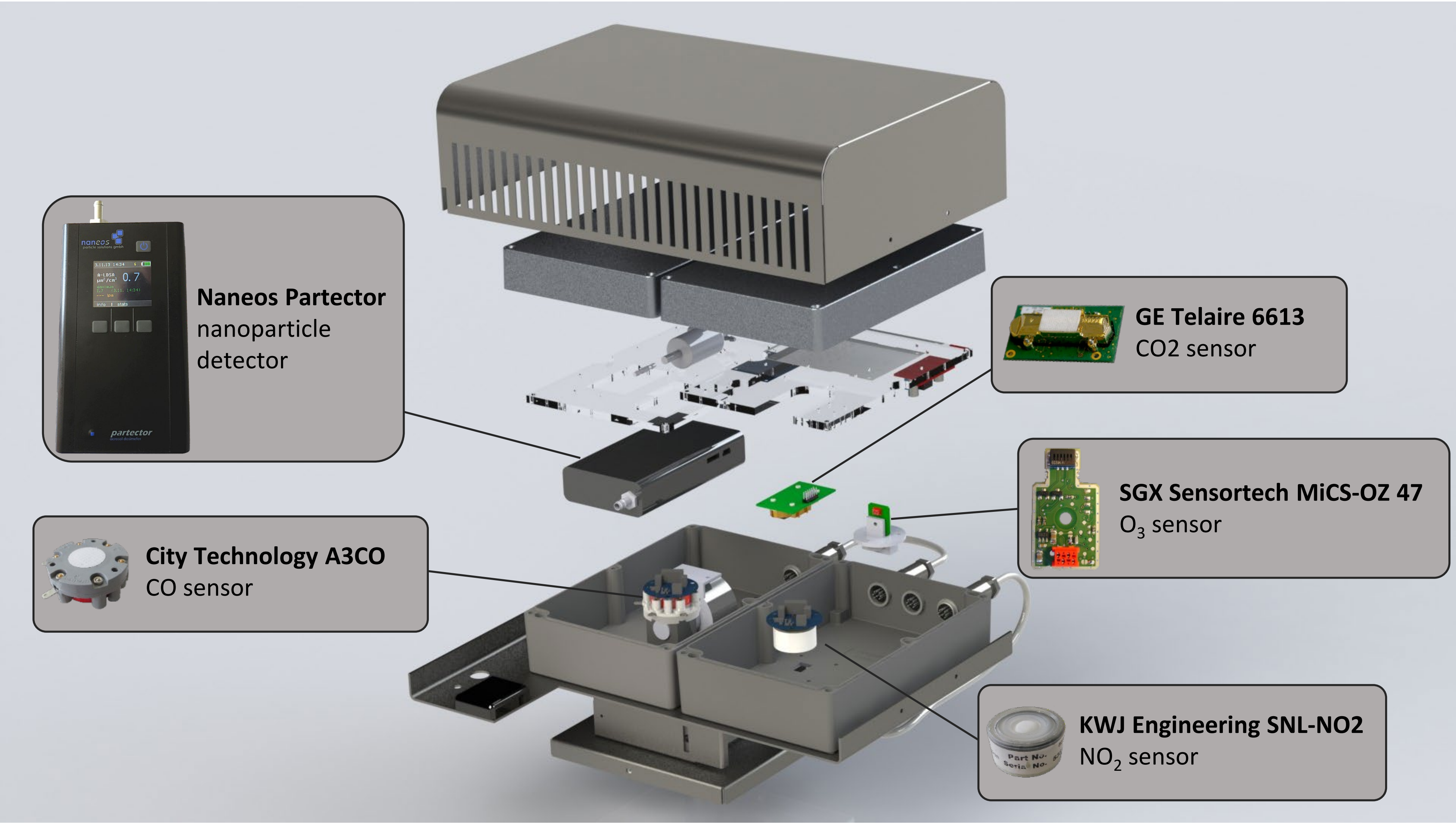
Air Sampling

Gas Sampler

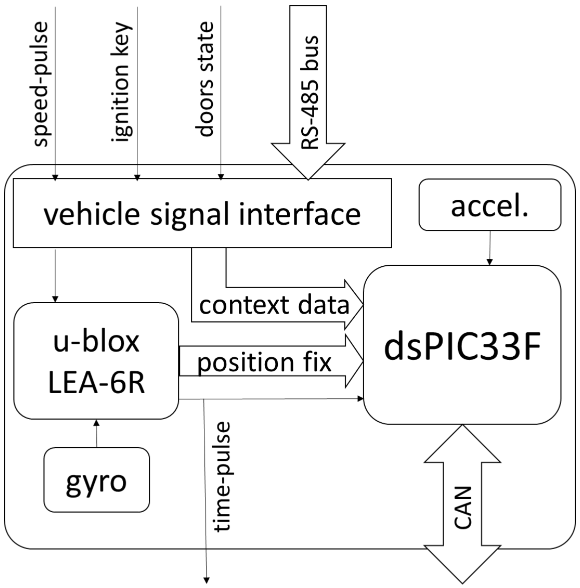
PM Sampler

CAN Bus

Air Sampling



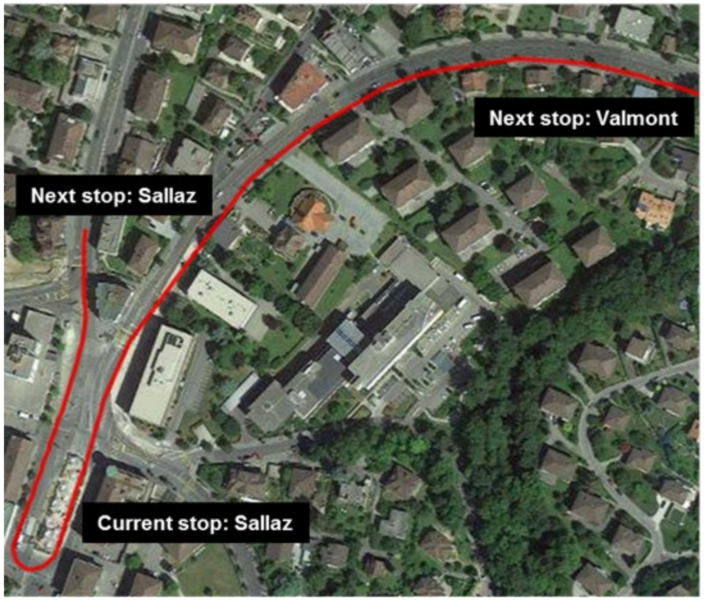
Localization

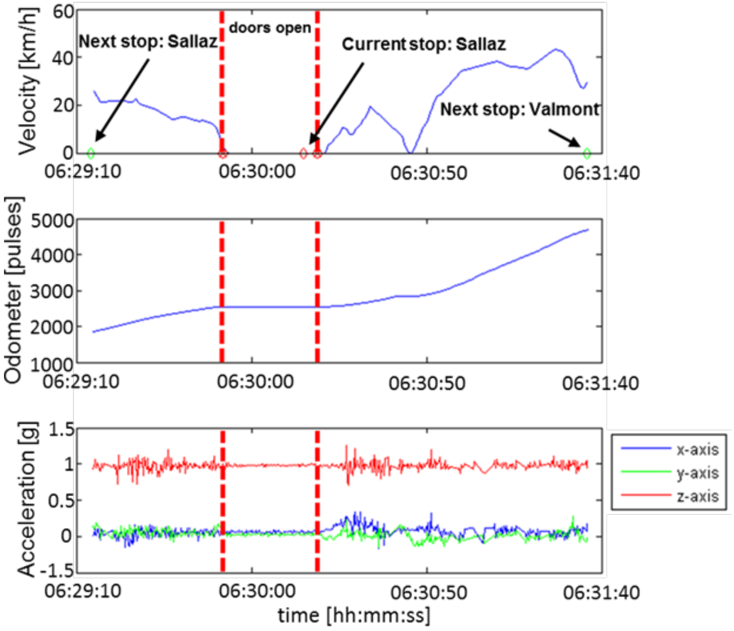


Based on **u-blox LEA-6R** module (fusion of GNSS + dead reckoning)

Additional features:

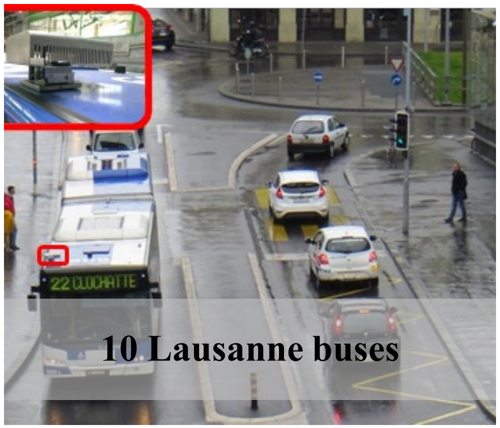
- 3-axis accelerometer
- Vehicle context data



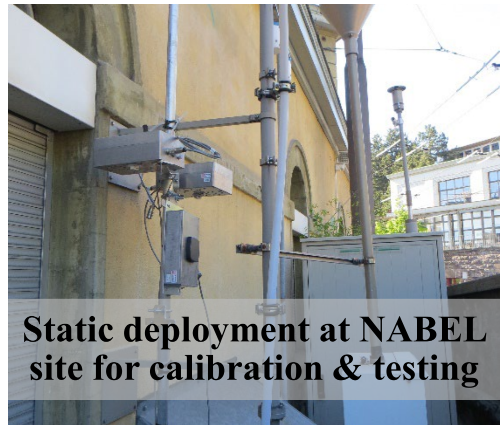


The Sensor Network

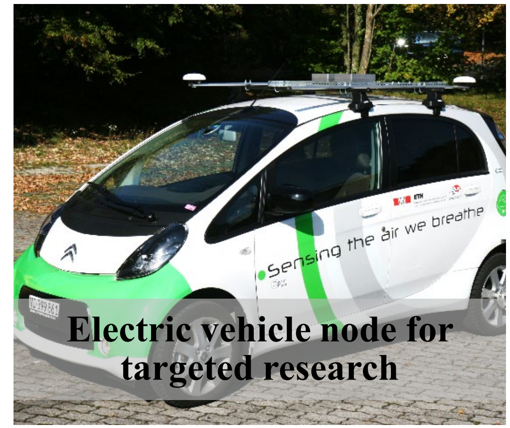
In the field



10 Lausanne buses

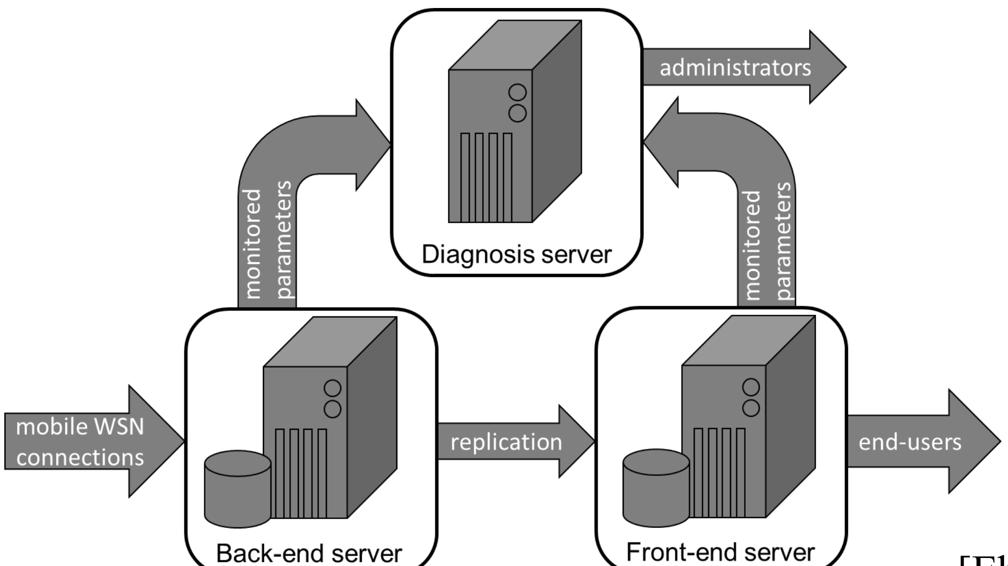


Static deployment at NABEL site for calibration & testing



Electric vehicle node for targeted research

Server-side



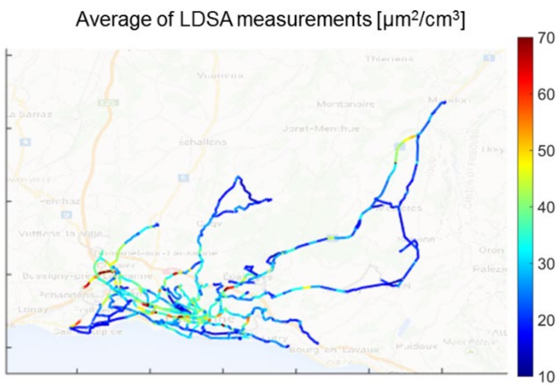
[Eberle, EPFL PhD thesis 2016]

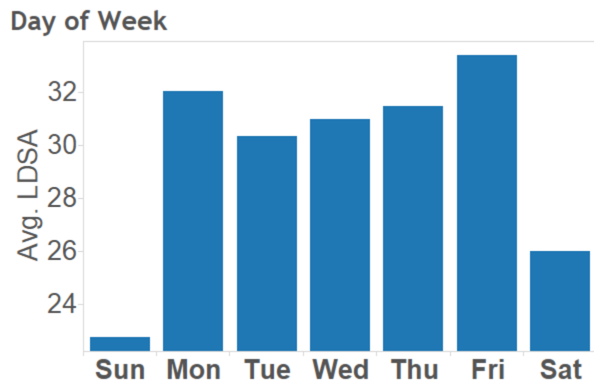
EPFL

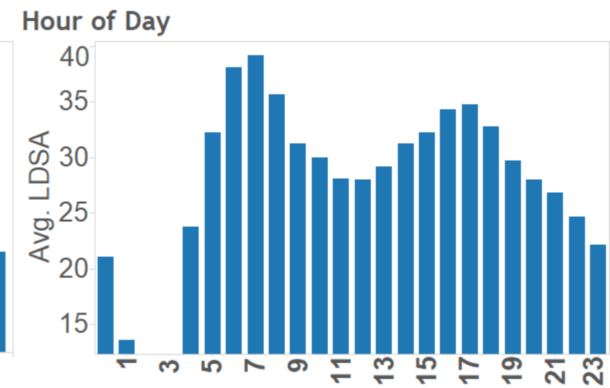
System Performance

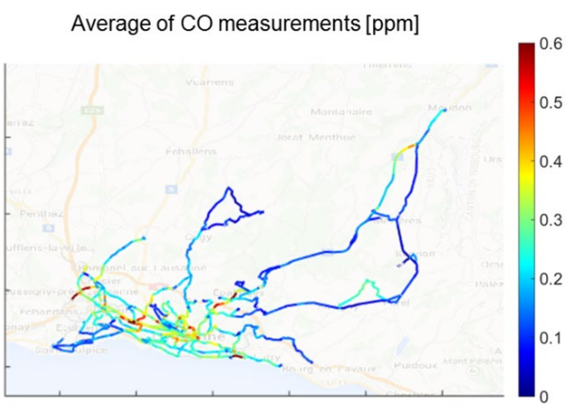
Disal

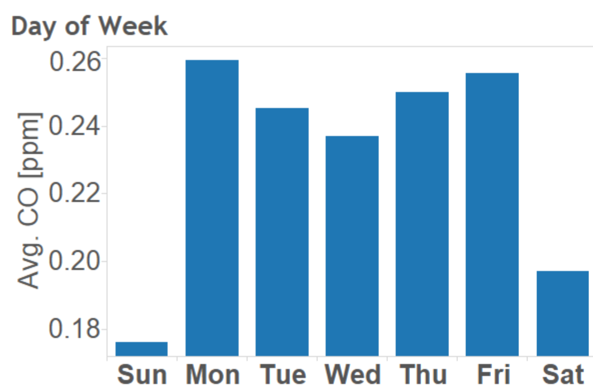
Spatio-temporal variability

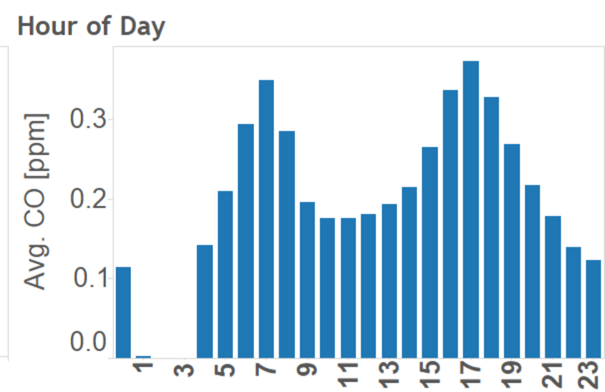






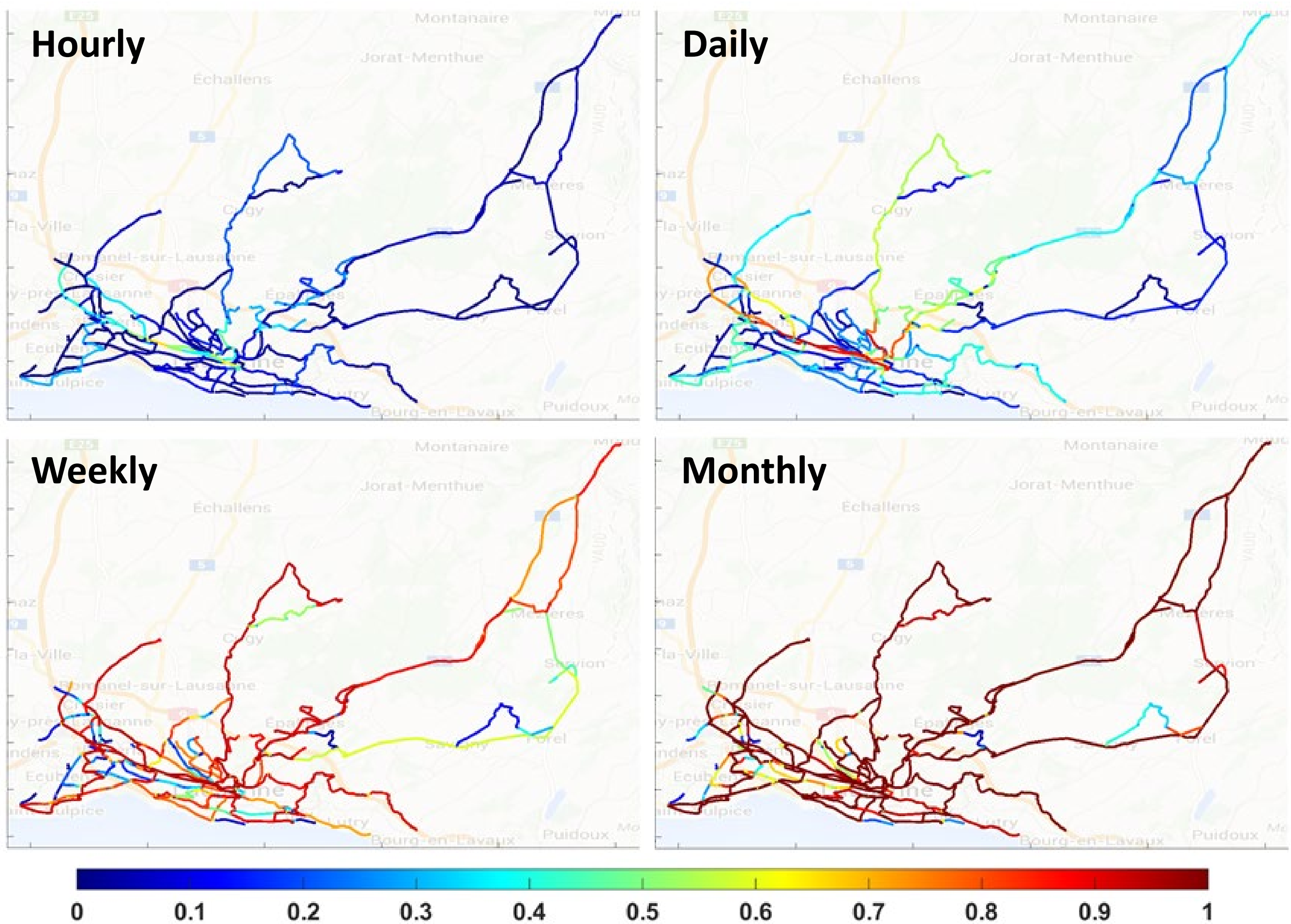






System Performance

Coverage



Coverage probability of the network

System Performance

Data throughput

Deployment start: October 22, 2013 (~ 3 years), numerical values on Sep 28, 2016

Measurement	Sampling rate	# of measurements
LDSA (PM)	1 s	> 203 million
[CO, NO_2, CO_2]	5 s	> 101 million
[O_3, temp., RH]	5 s	> 71 million
GPS fix	1 s	> 325 million
[odometer, accelerometer]	0.25 s	> 1352 million
vehicle context info	event-driven	> 14 million

[Arfire, EPFL PhD Thesis, 2016]

System Design → Mobility → Calibration → Mapping

Contributors: Adrian Arfire, Ali Marjovi

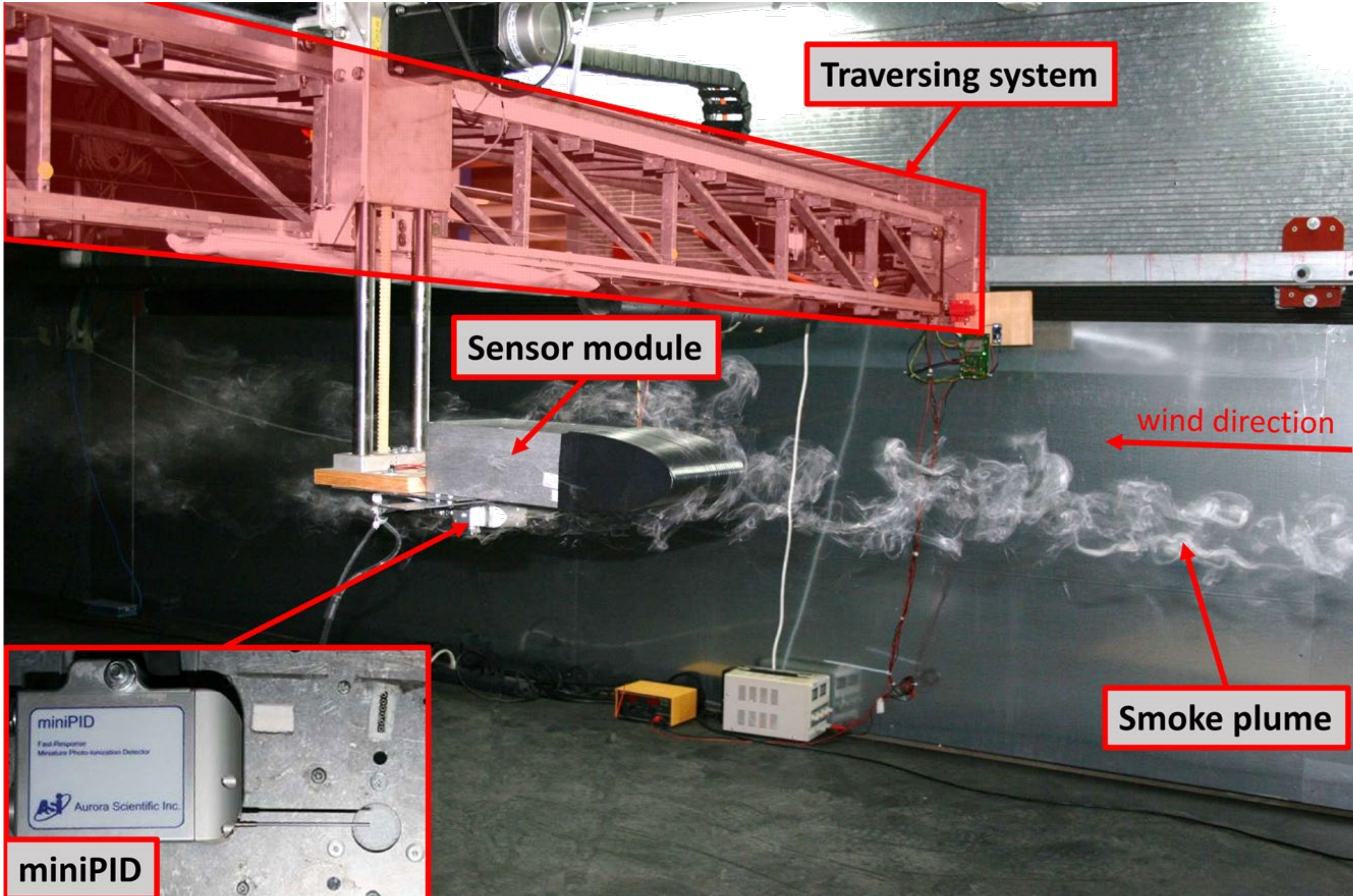
Mobility Effects

- Except for work in robot olfaction, largely unaddressed

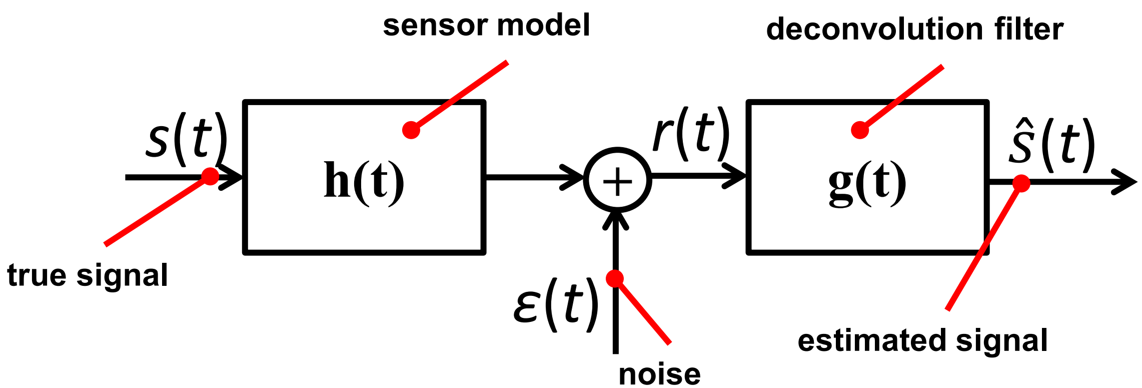
Strategies:

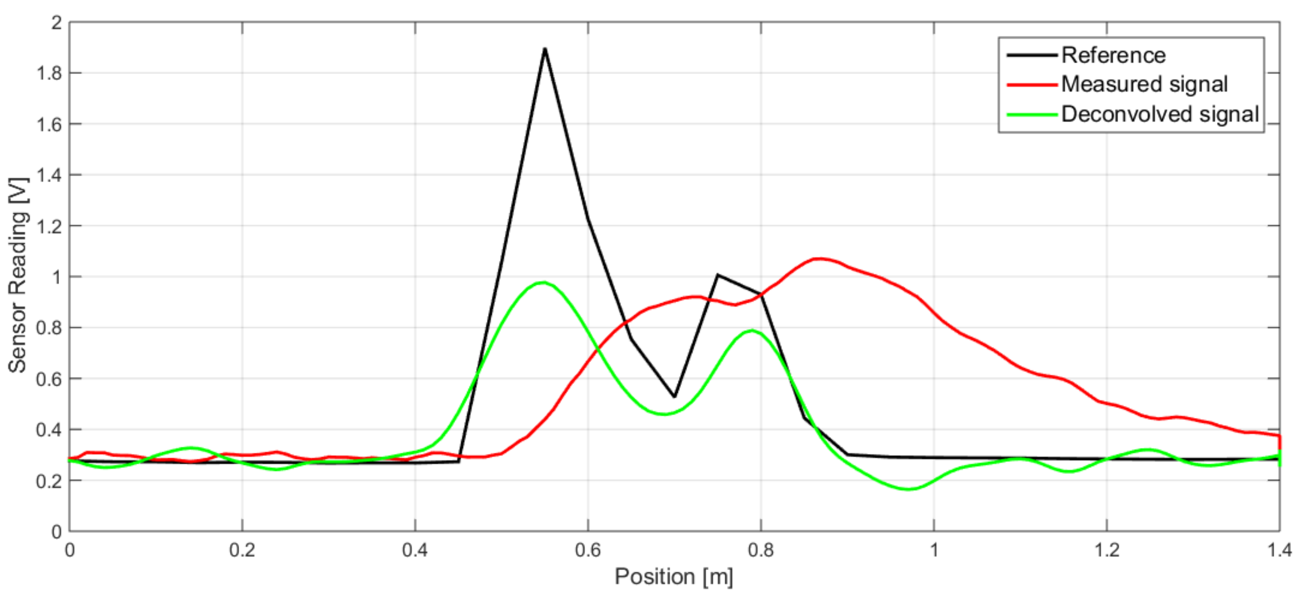
- Limiting robot velocity
- Cycling between movement & stationary measurement
- Customized **air sampling systems**

Experimental Set-up



Signal Reconstruction through Deconvolution

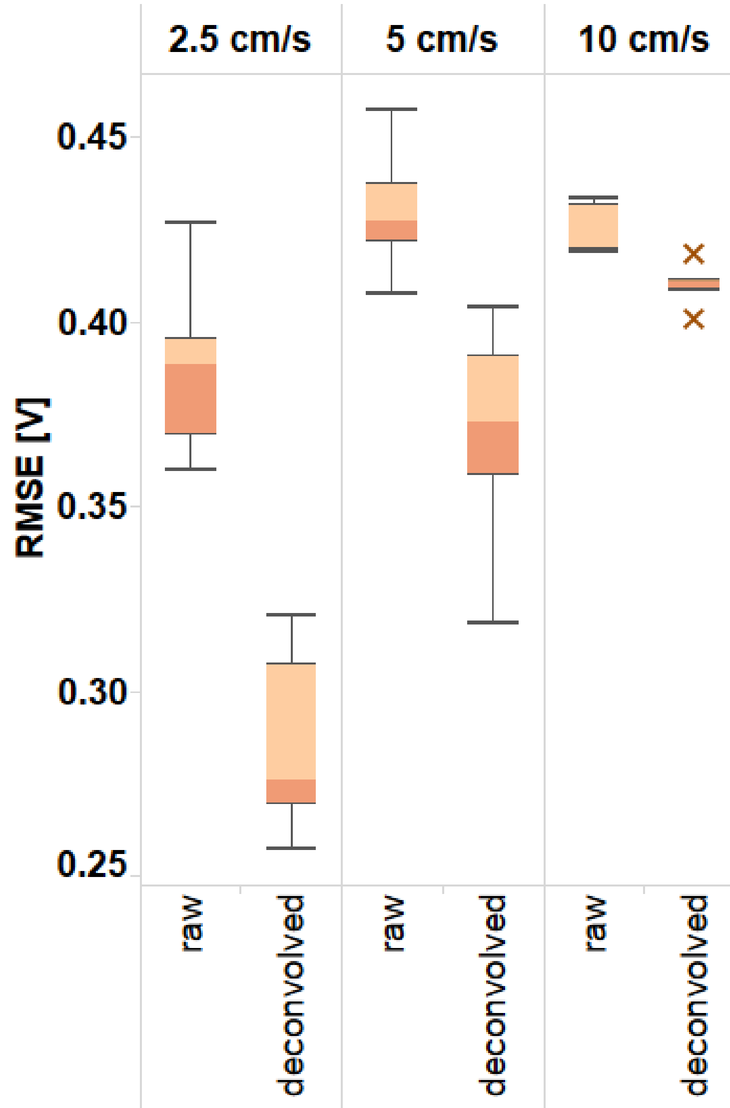




Signal Reconstruction through Deconvolution

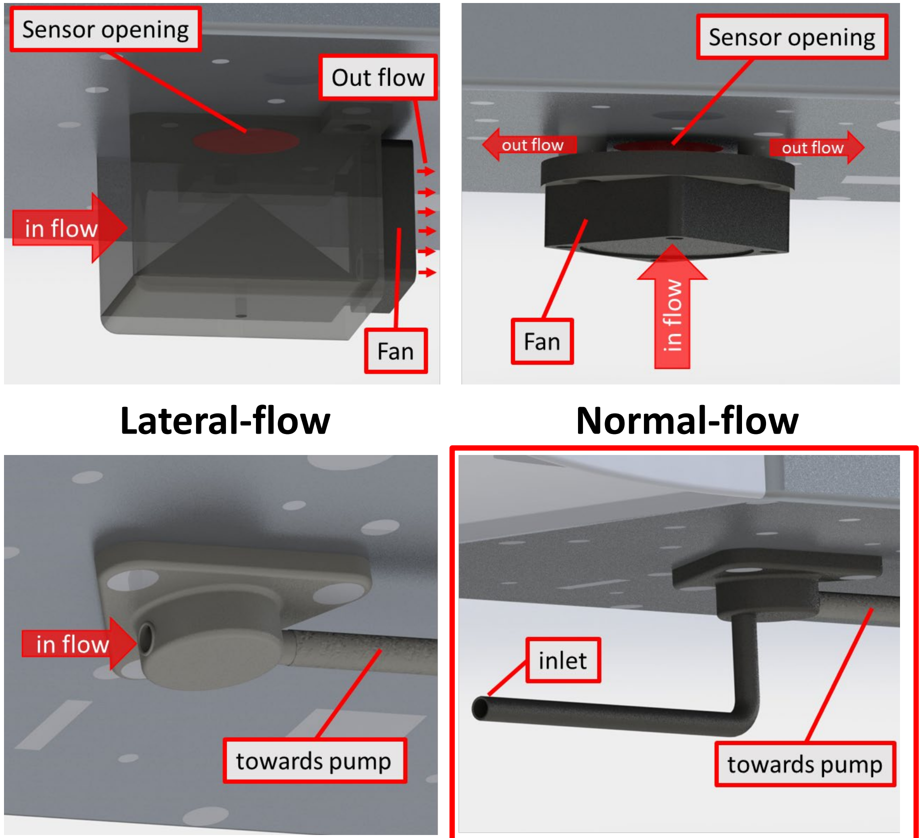
Results

- Consistent performance improvement
- Reduction of RMSE drops as the speed increases (SNR decreases)



Active Sampling System Design

Actuation: axial fans, diaphragm pumps



Lateral-flow

Normal-flow

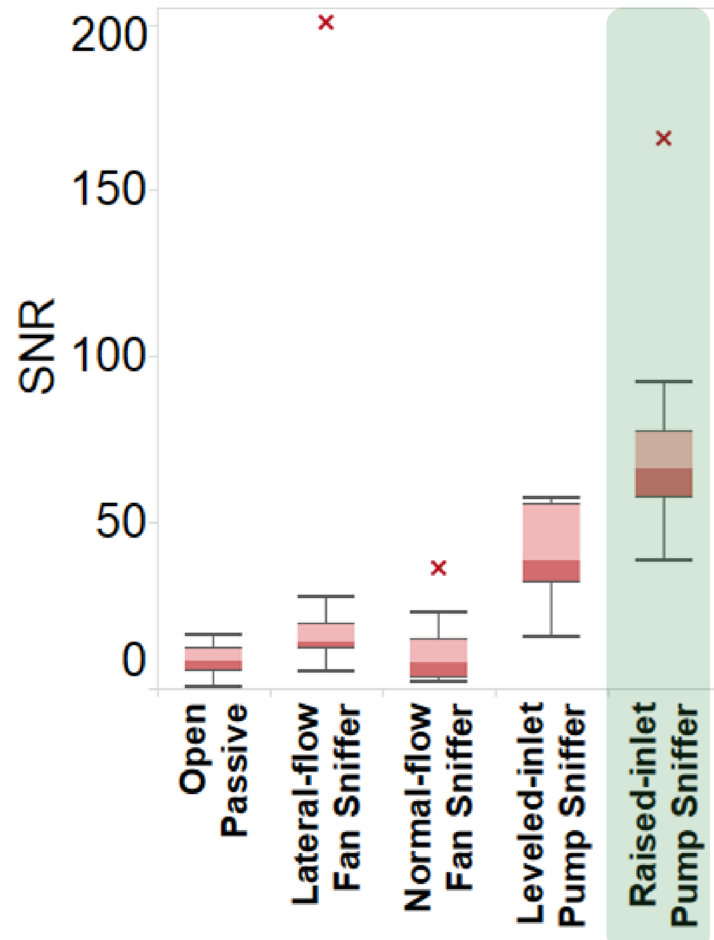
Leveled-inlet

Raised-inlet

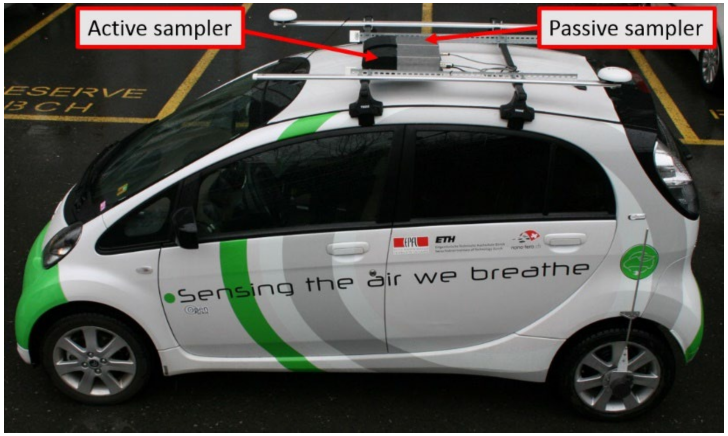
Air Sampling System Comparison

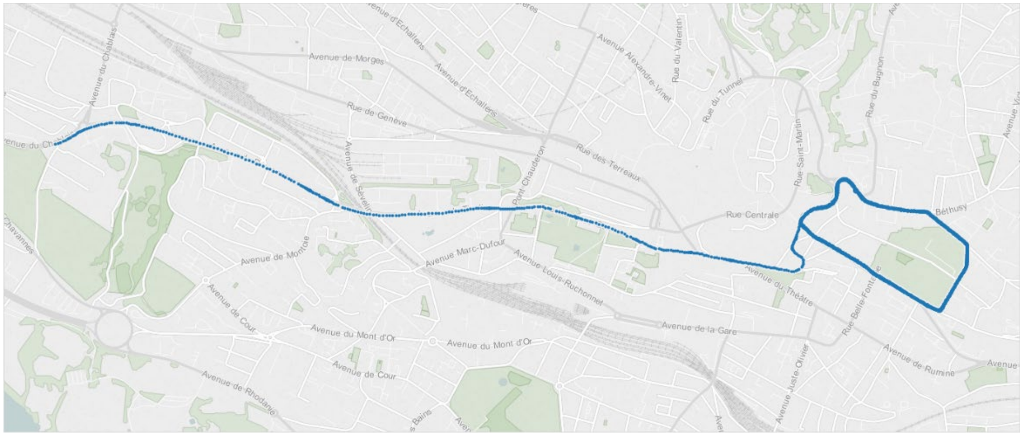
Results

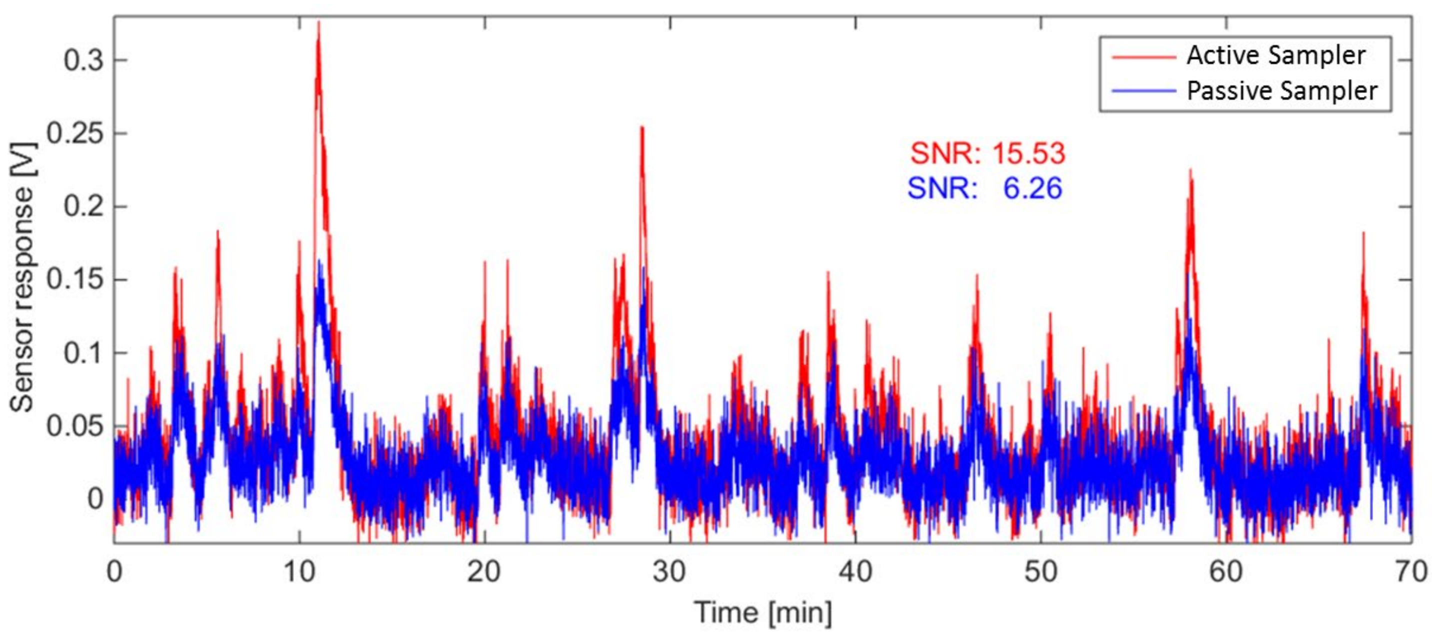
- Best performance: **pump-based sniffers**



Outdoor Experimental Validation







[Arfire et al., AIM 2016, EWSN 2016]

System Design → Mobility → Calibration → Mapping

Contributors: Ali Marjovi, Adrian Arfire, Loïc Frund, Fabrizzio Gonzales, Thomas Coral, Jonathan Giezendanner

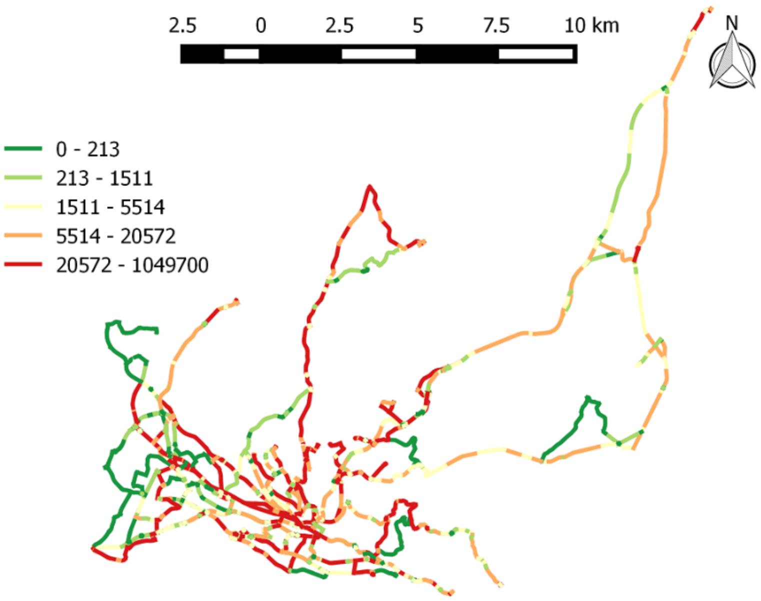
Mapping Problem

- LDSA data is sparse
- Coverage of sensors is incomplete and dynamic

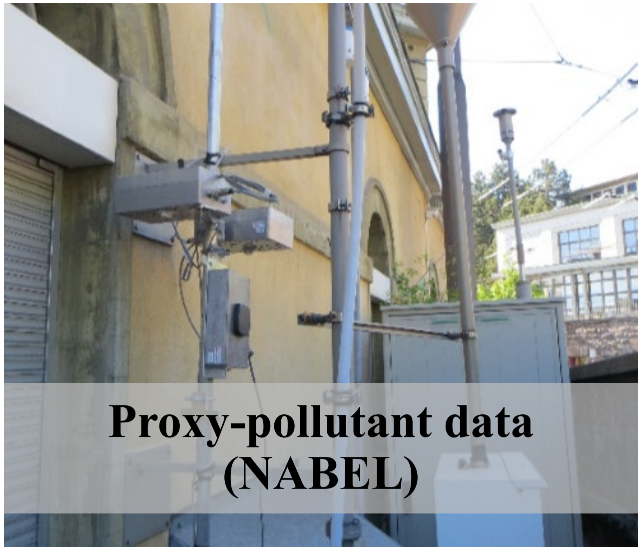
- Generating complete maps is a challenge.

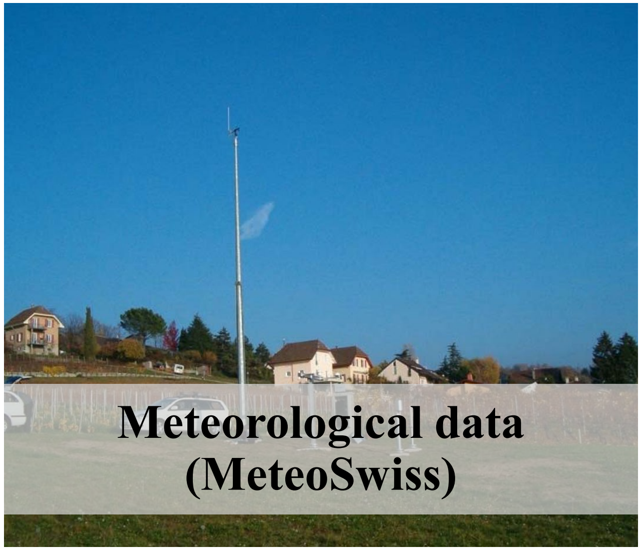
Solution:

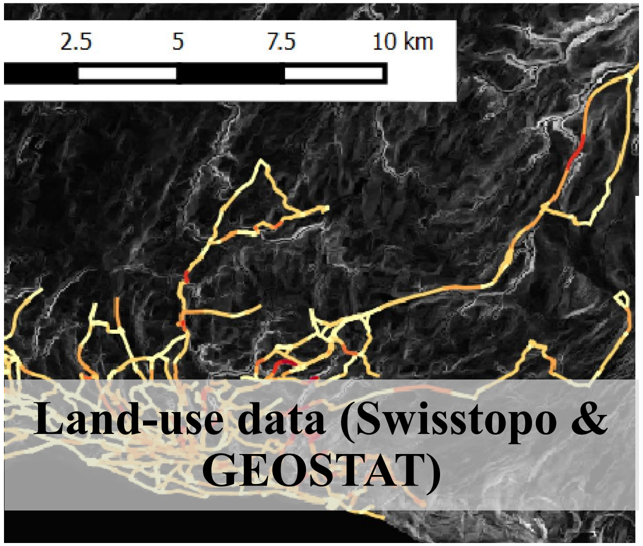
- Other sources of data is required
- Models are required to estimate the LDSA in locations/times of interest

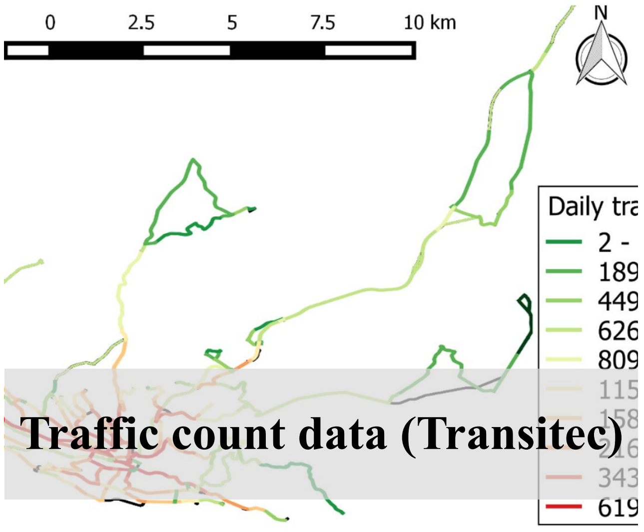


Explanatory Variables

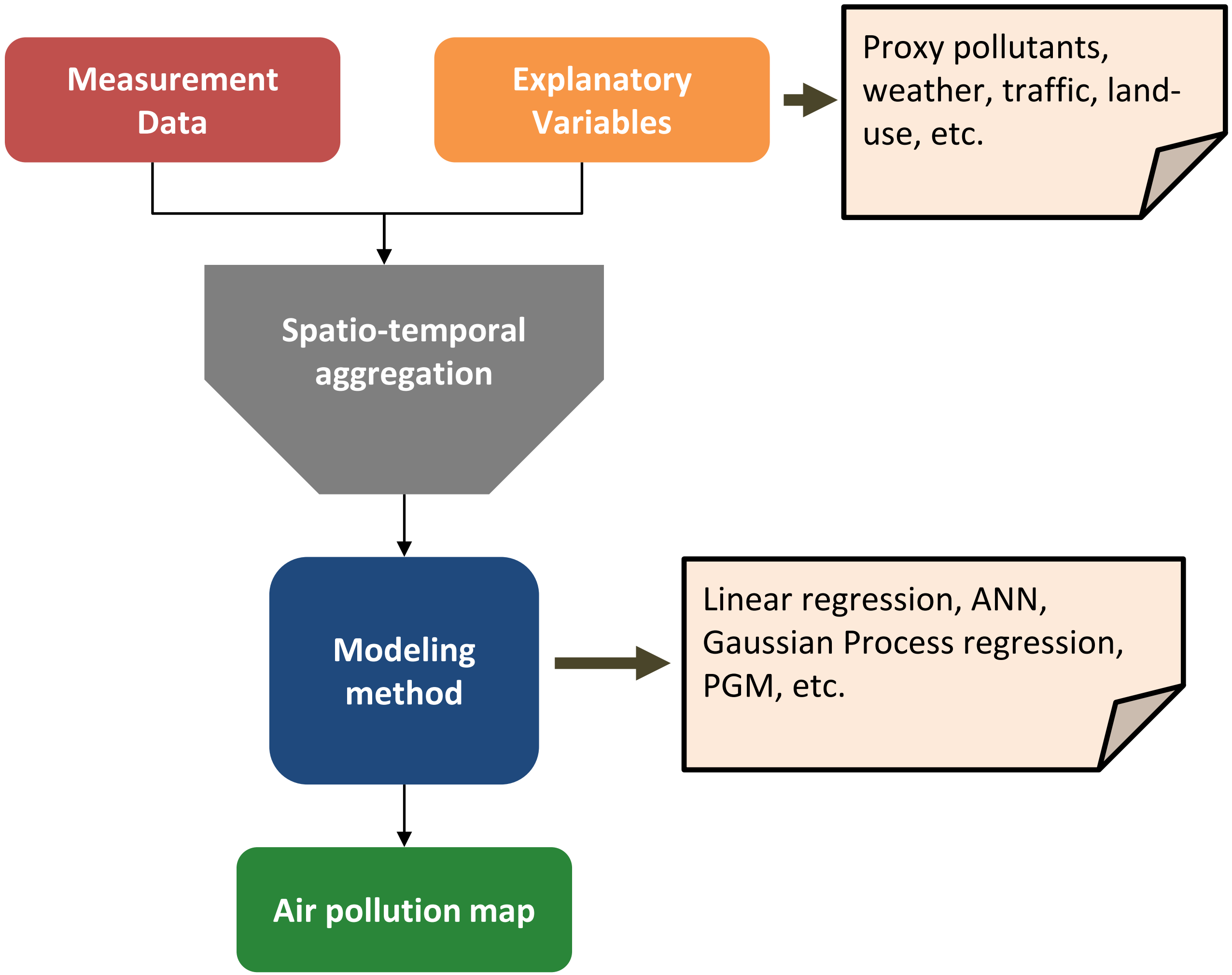








Statistical Modeling - Overview



Modeling Methods

Local models

Basic Log-Linear (BLL) regression

$$\log(L_m) = \alpha_0 + \sum_{i=1}^{9} \alpha_i \cdot \log(v_i)$$

Network-based Log-Linear (NLL) regression

- Dependency network – measurement correlation & complementarity

$$\log(L_{S_m}) = \alpha + \sum_{i=1}^{9} \beta_i \cdot \log(v_i) + \sum_{[m-n]\in E'} \delta_n \cdot \log(L_{S_n})$$

Global models

Basic Log-Linear with Land-Use (BLL-LU) regression

$$\log(L_{S_m}) = \alpha + \sum_{i=1}^{9} \beta_i \cdot \log(v_i) + \sum_{i=1}^{17} \gamma_i \cdot \log(U_{i,S_m})$$

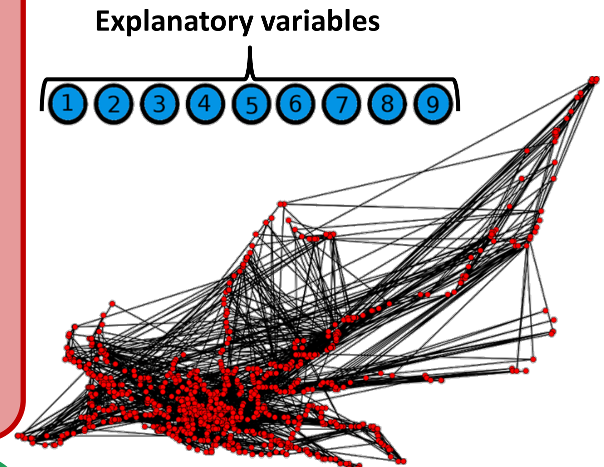
Land-Use Network-based Log-Linear (LU-NLL) regression

- Dependency network – land-use data

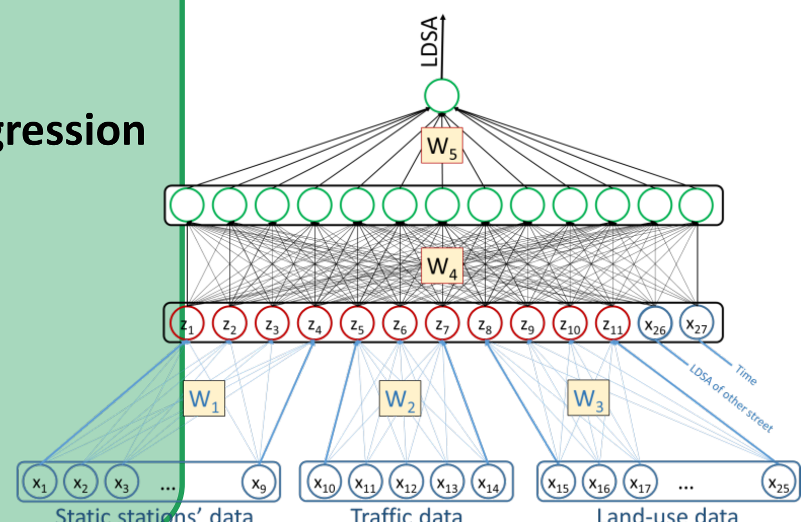
$$\log(L_{S_m}) = \alpha + \sum_{i=1}^{9} \beta_i \cdot \log(v_i) + \sum_{i=1}^{17} \gamma_i \cdot \log(U_{i,S_m}) + \sum_{[m-n]\in E} \delta_n \cdot \log(L_{S_n})$$

Deep Learning Model (DLM)

- ANN training technique



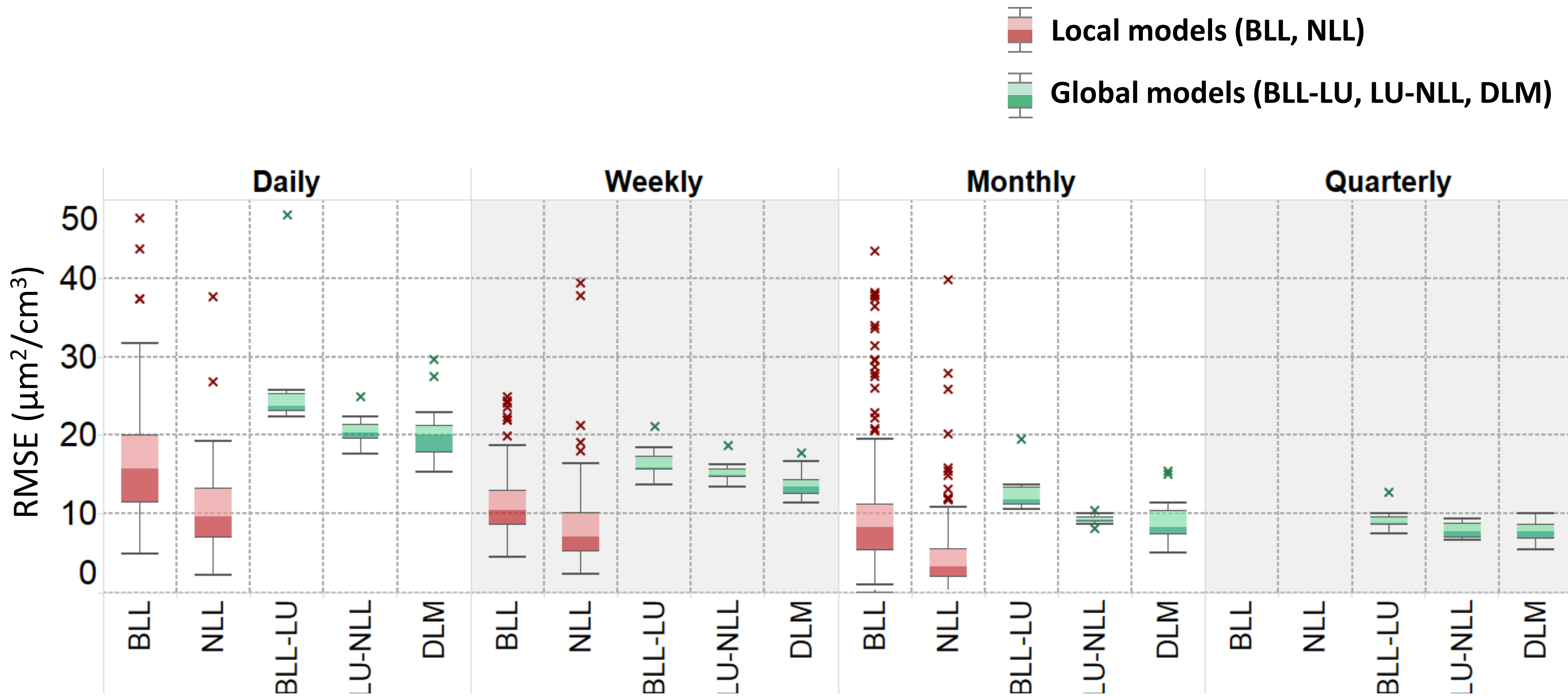
NLL dependency network



ANN structure for DLM method

Performance

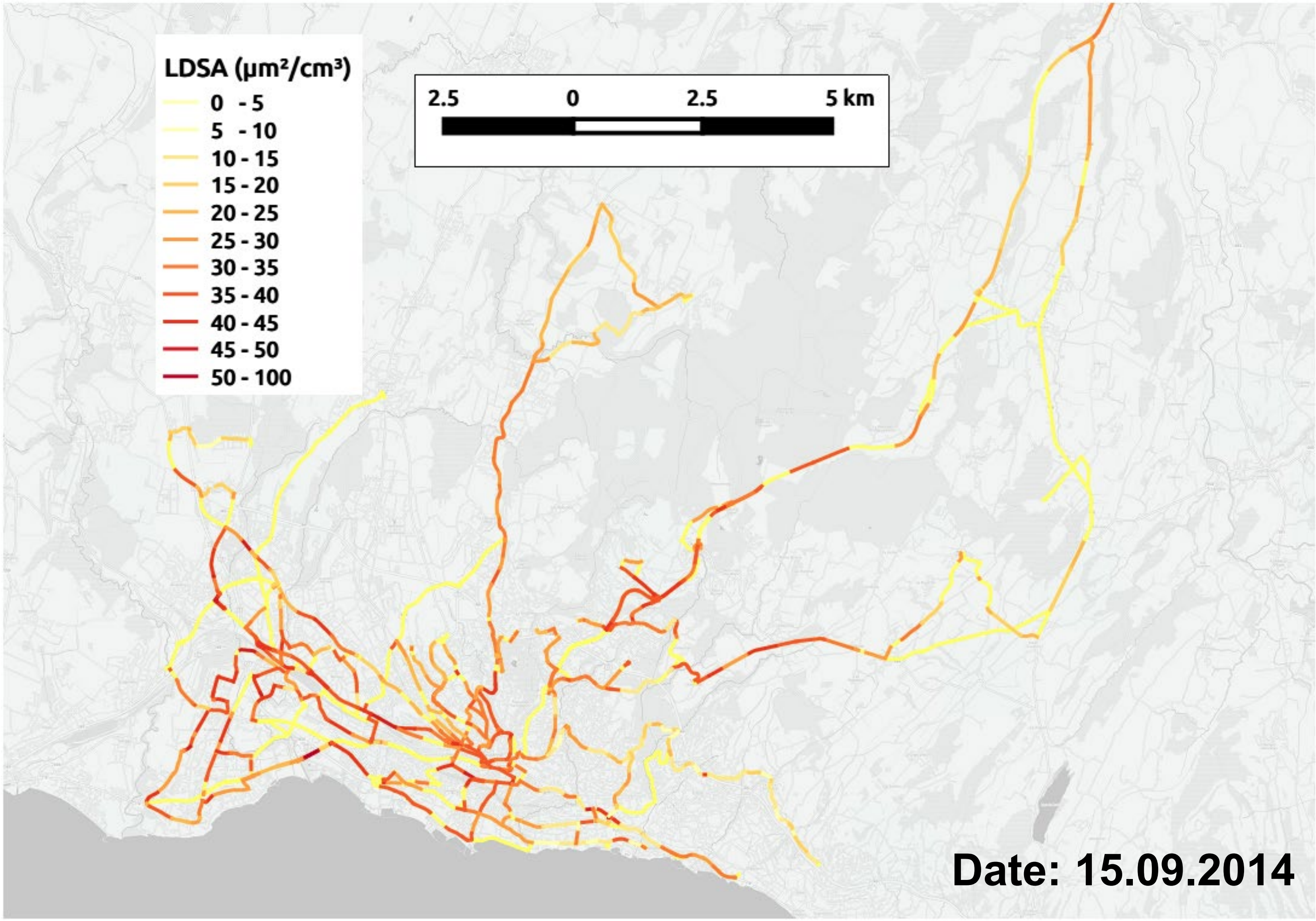
Results



[Marjovi et al., EWSN 17]

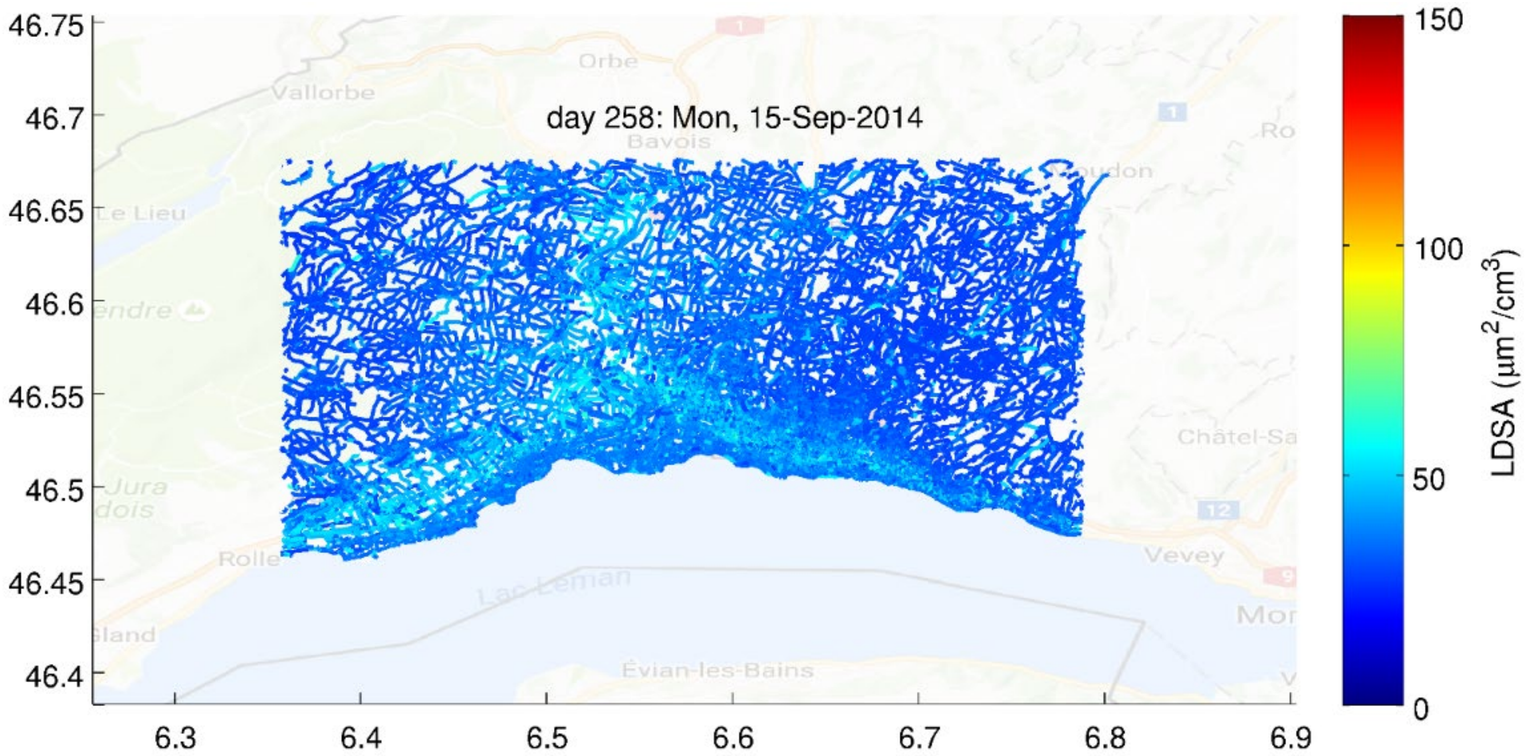
Pollution Map Example

Coverage extended to the regions where both land-use and traffic data is available, using DLM method (global model) for a given day.



Higher Resolution Maps

Without using traffic data



[Marjovi et al., unpublished]

Conclusion

Take Home Messages

- Mobility in sensor networks offers wider coverage with the same number of nodes and can bring advantages in deployment, gathering, and maintenance operations
- Depending on the sensing modality and technology, mobile nodes can bring additional challenges that eventually results in additional complexity at the node level
- Increasing the resolution of air pollution data is necessary for understanding health impact
- Data quality is critical in these type of applications, so appropriate techniques for handling drifting, low selectivity, and mobility impact on low-cost sensors are key
- The OpenSense project gathered probably the largest dataset on urban air quality in the world and pioneered the use of public transportation for mobile sensor networks

Additional Literature – Week 12

Pointers

- OpenSense:
  - https://archiveweb.epfl.ch/nanotera.epfl.ch/projects/214.php.html
  - https://archiveweb.epfl.ch/nanotera.epfl.ch/projects/423.php.html
- Breathe London: https://www.breathelondon.org/

Articles

- Lai T. T.-T., Chen W.-J., Chen Y.-H. T., Huang P., and Chu H.-H., “Mapping Hidden Water Pipelines Using a Mobile Sensor Droplet”, *ACM Trans. Sensor Networks*, 9(2): Article 20, 2013.
- Schwager M., Detweiler C., Vasilescu I., Anderson D. M., and Rus D., “Data-Driven Identification of Group Dynamics for Motion Prediction and Control”. *J. of Field Robotics,* 25(6-7):305-324, 2008.
- Marjovi A., Arfire A., and Martinoli A., “High Resolution Air Pollution Maps in Urban Environments using Mobile Sensor Networks”. Proc. of the 11th International Conference on Distributed Computing in Sensor Systems, June 2015, Fortaleza, Brazil, pp. 11-20.
- B. Maag, O. Saukh, D. Hasenfratz, L. Thiele, “Pre-Deployment Testing, Augmentation and Calibration of Cross-Sensitive Sensors”, *Proc. of the International Conference on Embedded Wireless Systems and Networks*, February 2016, Graz, Austria, pp. 169-180.
- D. Hasenfratz, O. Saukh, C. Walser, C. Hueglin, M. Fierz, T. Arn, J. Beutel, and L. Thiele, “Deriving high-resolution urban air pollution maps using mobile sensor nodes,” *Pervasive and Mobile Computing*, vol. 16, pp. 268–285, 2015.
- Saukh O., Hasenfratz D., and Thiele L., “Reducing Multi-Hop Calibration Errors in Mobile Sensor Network”. *International Conference on Information Processing in Sensor Networks*, pp. 274-285, 2015.
- Berchet A., Zink K., Muller C., Oettl D., Brunner J., Emmenegger L., and Brunner D., “A cost-effective method for simulating city-wide air flow and pollutant dispersion at building resolving scale”. *Atmospheric Environment*, vol. 158, pp. 181–196, 2017.