Filling the Gaps in Urban Air Pollution Monitoring
with Google Street View Cars

Presenter: **Joshua Apte**
JSApte@utexas.edu
University of Texas at Austin
Department of Civil, Architectural
and Environmental Engineering

HEI | 01 May 2017

Research Partners

aclima™

EDF ENVIRONMENTAL DEFENSE FUND®
Finding the ways that work

Google Earth Outreach

TEXAS

BERKELEY LAB

Berkeley UNIVERSITY OF CALIFORNIA

BAY AREA AIR QUALITY MANAGEMENT DISTRICT

West Oakland Environmental Indicators Project
know which way the wind blows

Utrecht University

Co-authors:

Kyle Messier, Shahzad Gani, Melissa Lunden, Roel Vermeulen,
Julian Marshall, Tom Kirchstetter, Michael Brauer, Chris Portier, Steven Hamburg

Issue: ambient ≠ exposure

"Ambient": what we measure

Ambient monitors
are intentionally located
far from emissions sources

"Exposure": what we breathe

Graphic: Bennett et al., Environ. Sci. Technol., 2002

Ambient monitoring today

US EPA monitors for 25 largest U.S. urban areas

111 M people ~ 50% of urban population

	NO_2	O_3	$PM_{2.5}$
Number of sites	**132**	**185**	**282**
… per million people	1.2	1.7	2.5
… per 1000 urban km^2	1.6	2.2	3.4

Urban ambient monitors provide:

little spatial information

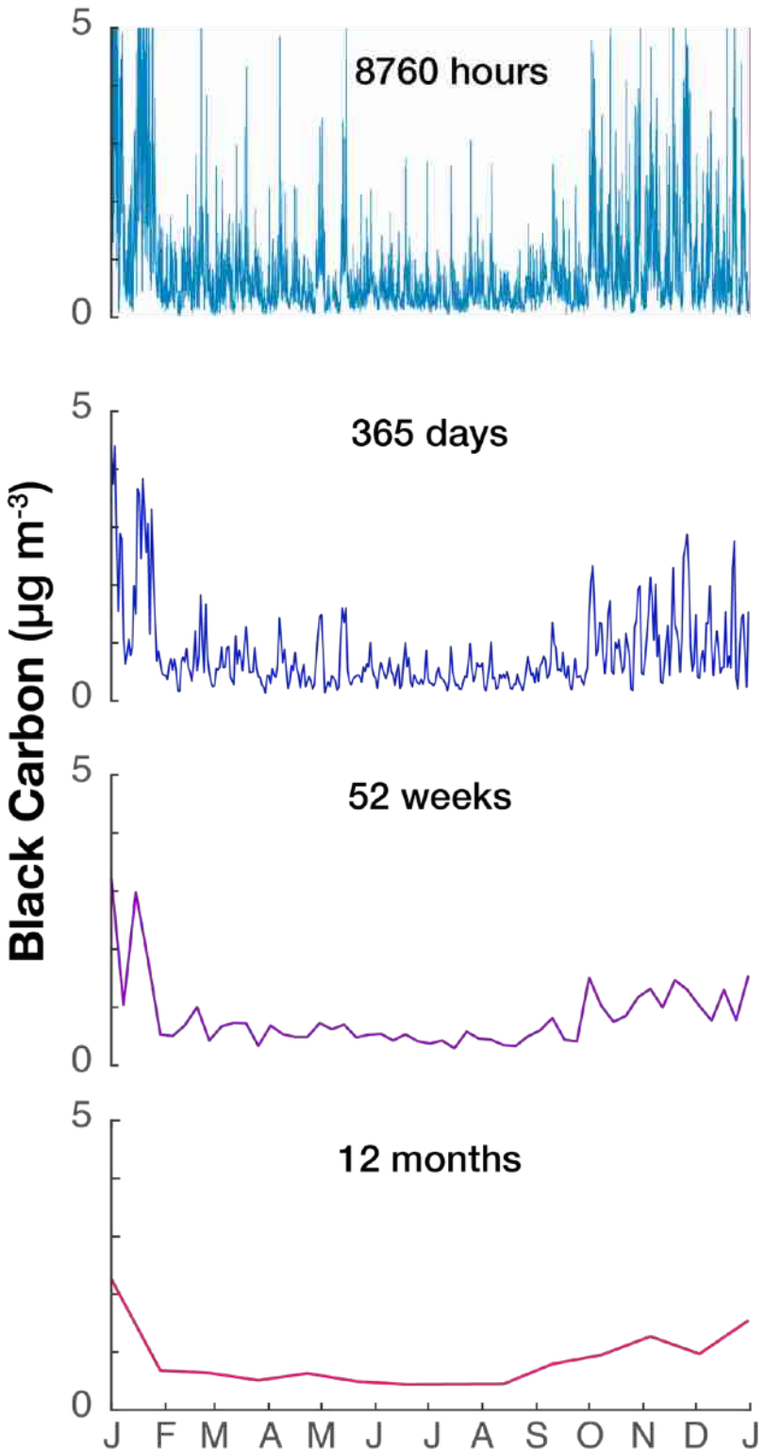
high precision/accuracy

excellent temporal coverage

Year-2015 US EPA network

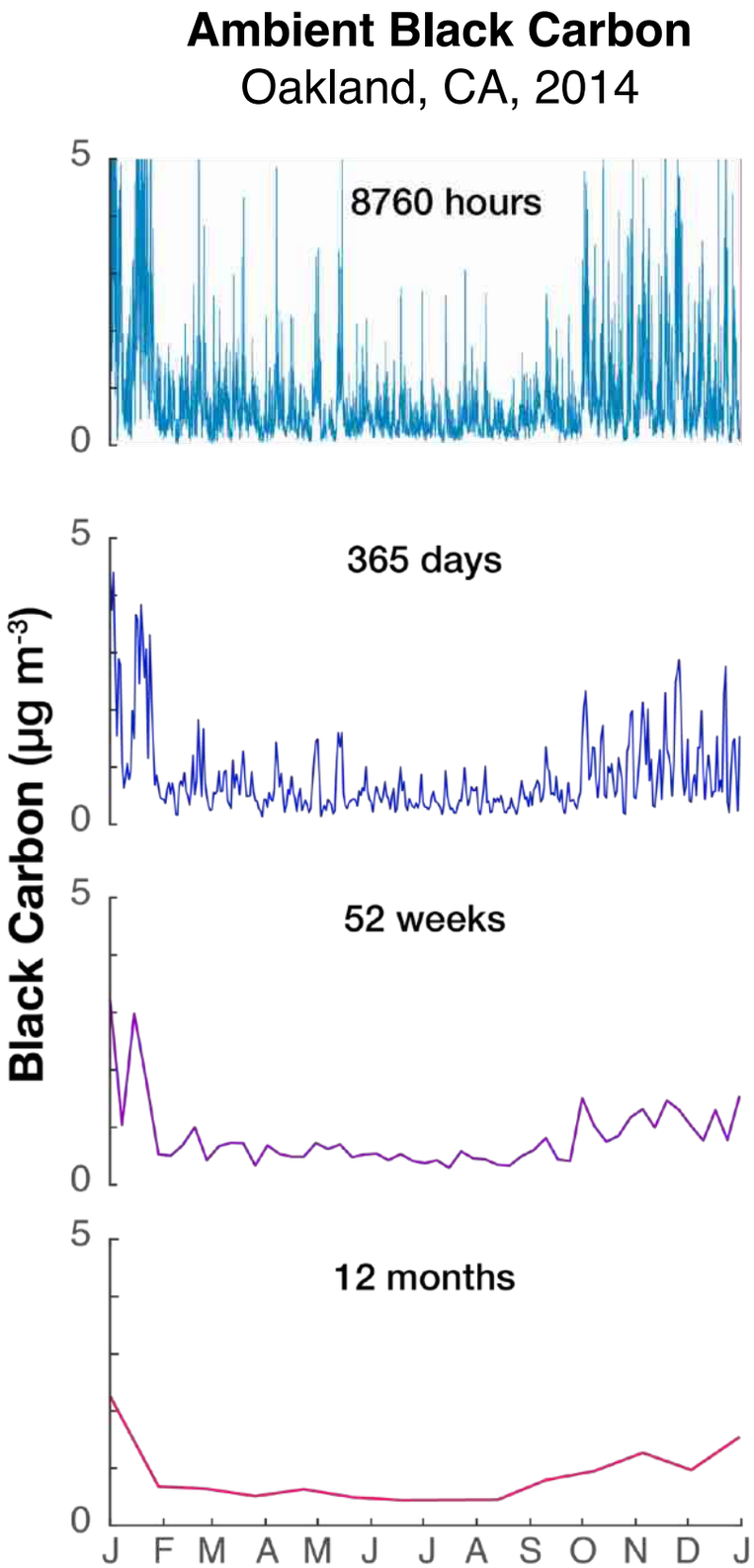
Don’t need much data to estimate annual average

Ambient Black Carbon
Oakland, CA, 2014



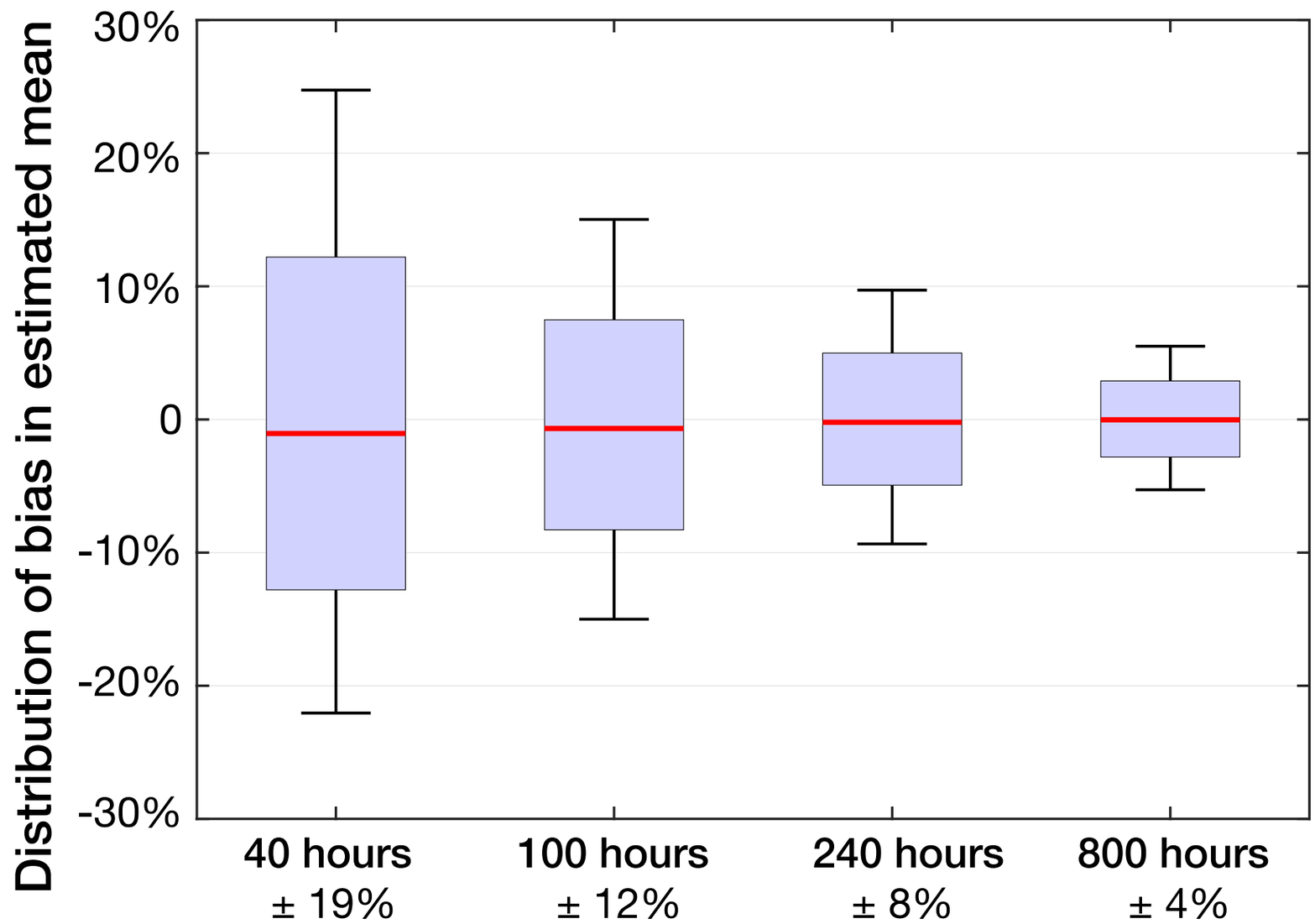
Inspired by: Tan et al., *Atmos Environ* 99, 333-340, 2014

Don’t need much data to estimate annual average



Randomly sample X hours of data

Compare sample mean with annual mean



Inspired by: Tan et al., *Atmos Environ* 99, 333-340, 2014

Can we trade

temporal coverage

for

spatial coverage?

Rich history of mobile monitoring

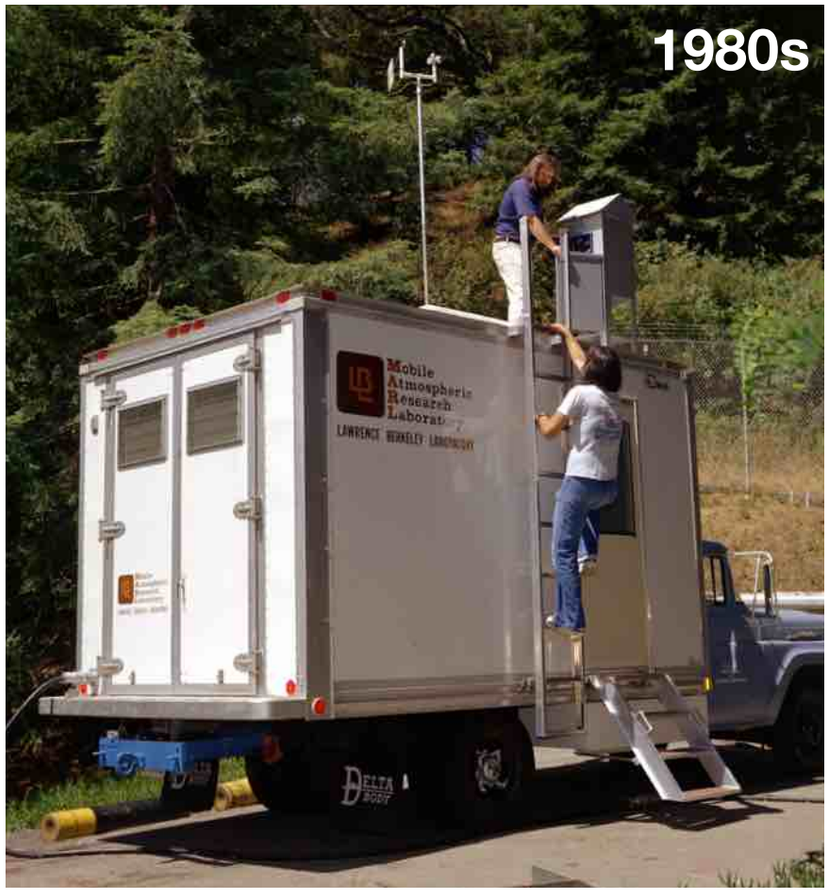
5+ decades of progress:

Advances in measurement technology

Increasing mobility of platforms

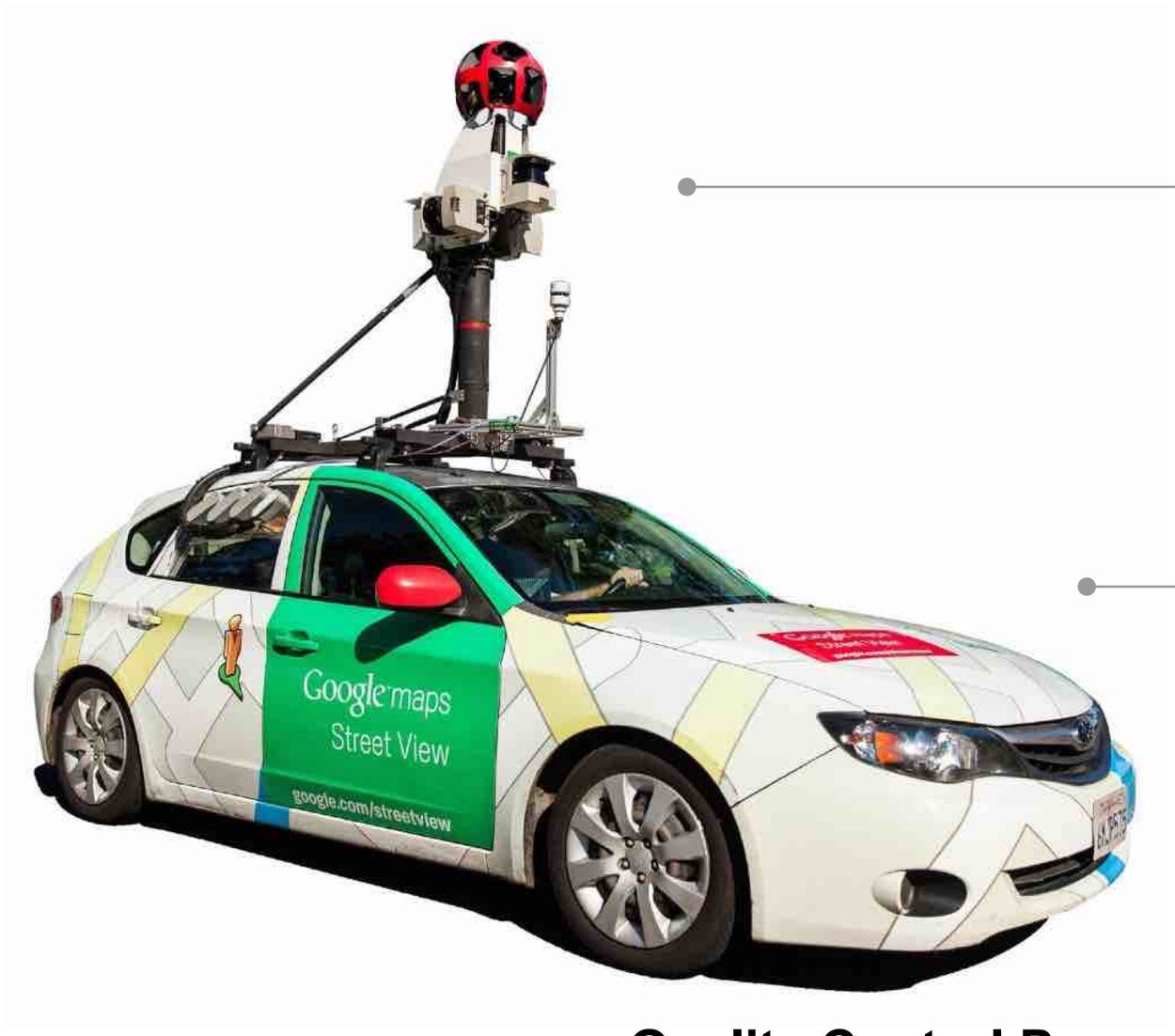
Shift in emphasis from atmosphere to exposure

Routine monitoring is still very challenging!



Photos: D. Ensor, 2011, CARB, LBNL

Towards *routine* mobile measurements



Location + Meteorology

Latitude & Longitude
Vehicle Speed and Heading
Wind Direction
Wind Speed
External Temperature
External Pressure

Lab-Grade Instrumentation

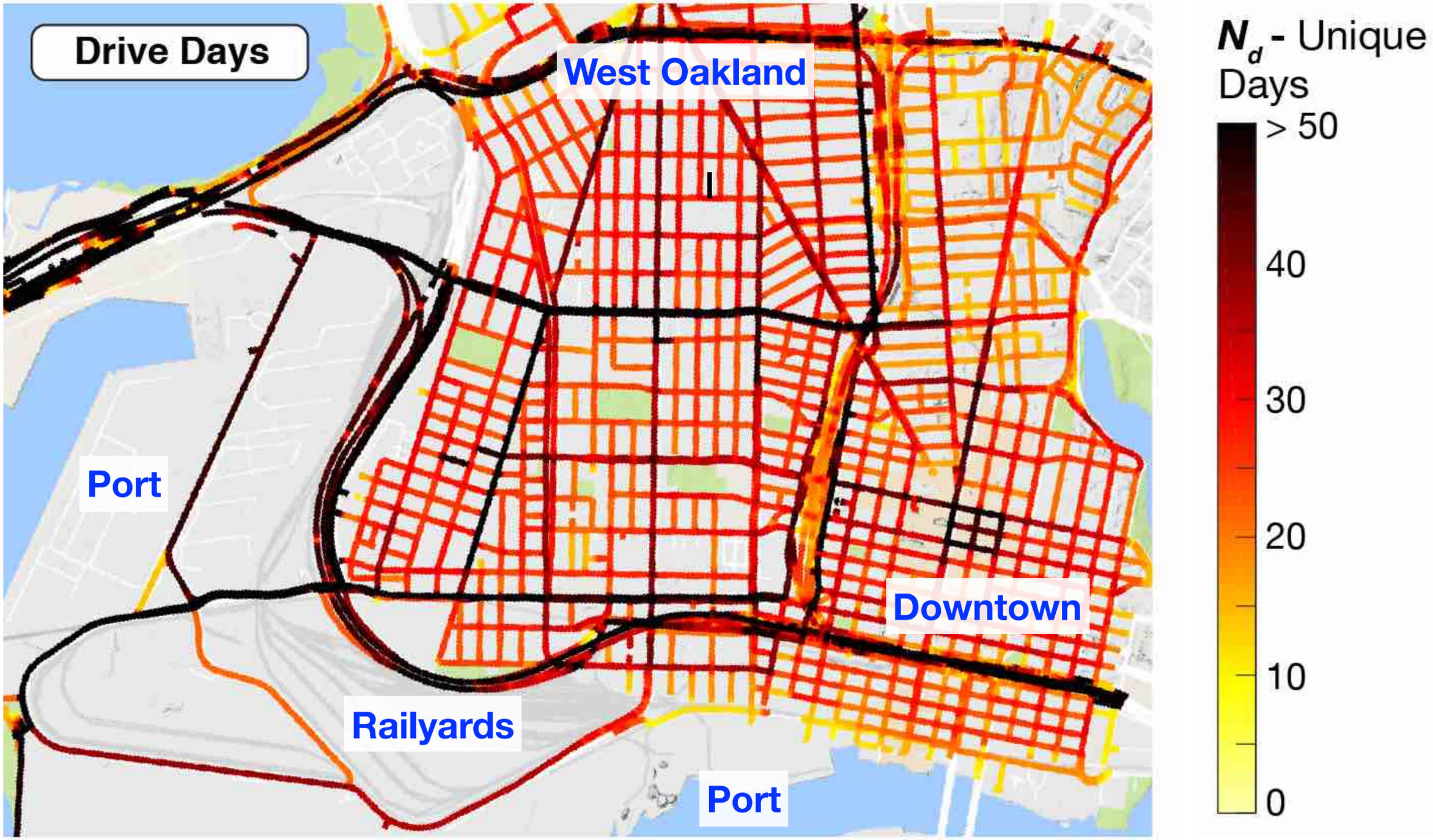
Black Carbon: photoacoustic extinction
Nitric Oxide: chemiluminescence
Nitrogen Dioxide: cavity-attenuation phase shift spectroscopy

Sample rate: 1 Hz

Quality Control Process | aclima Ei

Raw Data → Data Cleaning → Data Correction → Uncertainty Calculation → Qualified Data

Approach: repeat driving *overkill*



Median 30 m road segment: ~31 sampling days
daytime only, seasonally balanced

Data reduction approach

Repeat monitoring → persistent, stable spatial patterns

- Group measurements by 30 meter road segment
  - Average: ~31 days per road segment
  - ~100-200 1 Hz data points per road segments

- Compute median concentration for each road segment

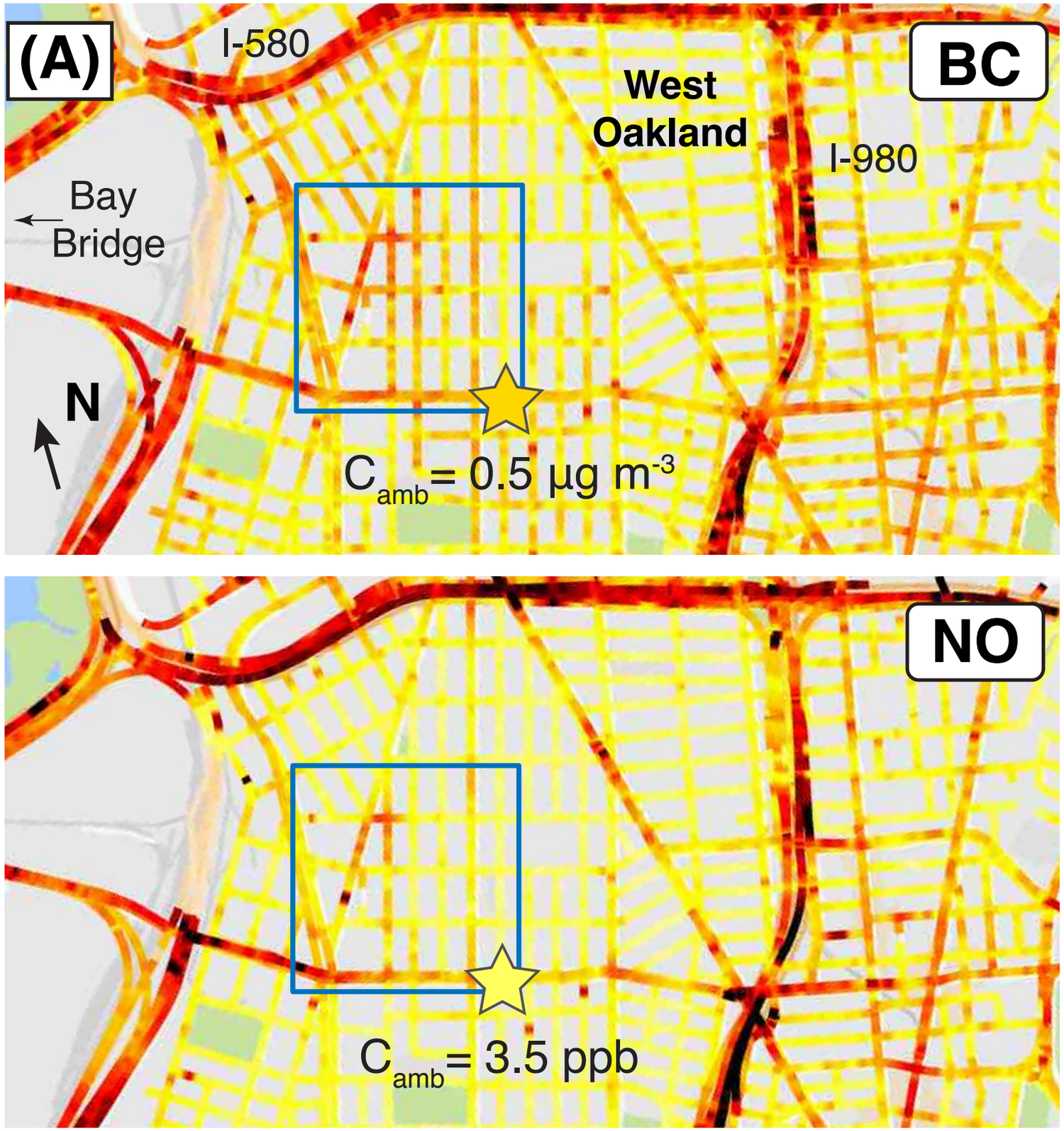
- High precision: ±10-20% of median based on bootstrap resampling

Mapping pollution at 30 m scale

Median weekday, daytime concentration from repeated drives

Neighborhood hotspots

Some key lessons



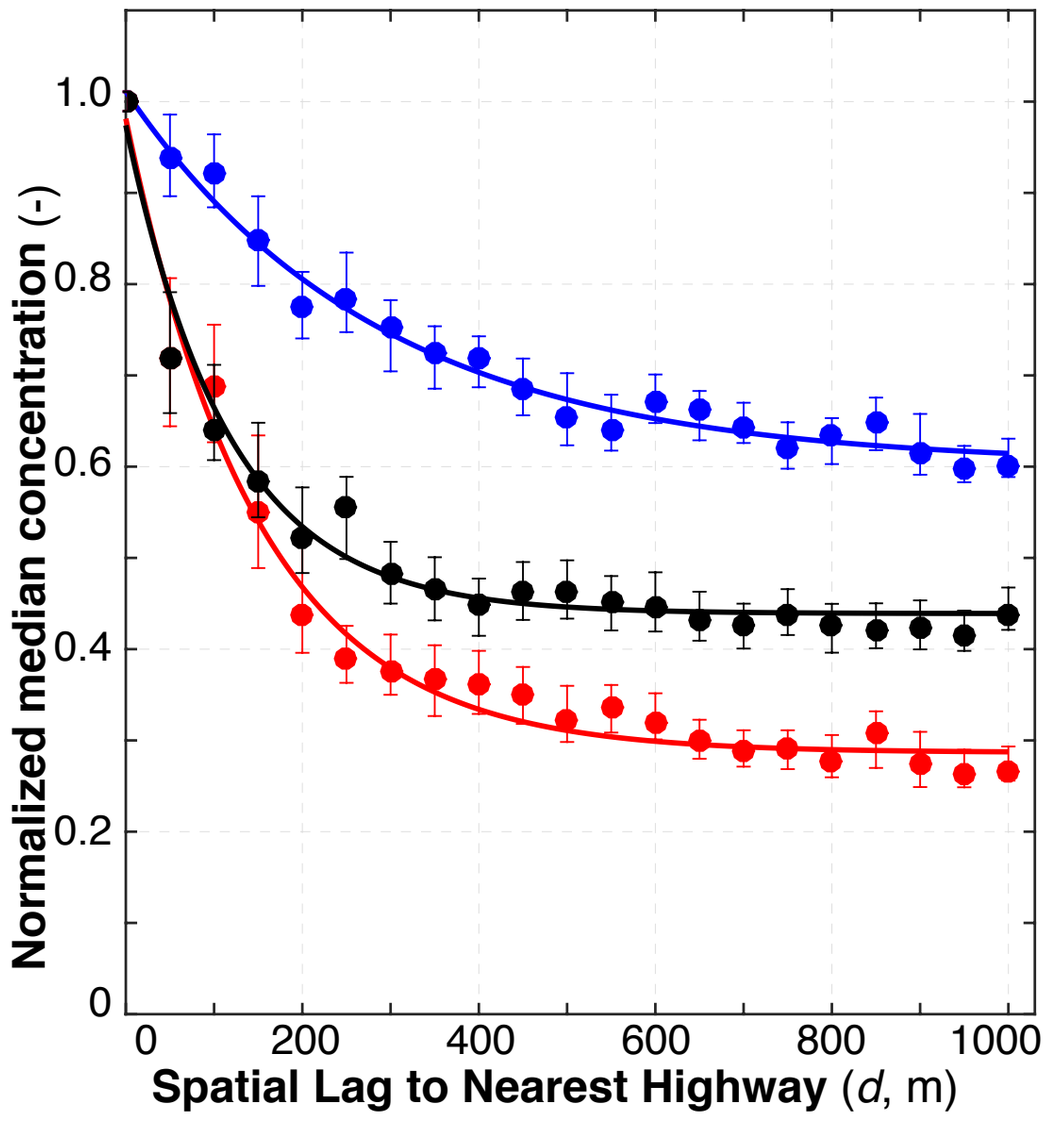
- Similar spatial patterns among 1° pollutants
- Ambient concentration ~ levels on quiet streets
- Looks a bit like a LUR— but it's measured, not predicted
- Ubiquitous, stable hotspots
- **~10^5× more spatial data!** 1 observation : 10 people

BC (µg m^{-3})
0 0.5 1.0 1.5 2.0
0 10 20 30 40
NO (ppb)

Spatiotemporal data mining

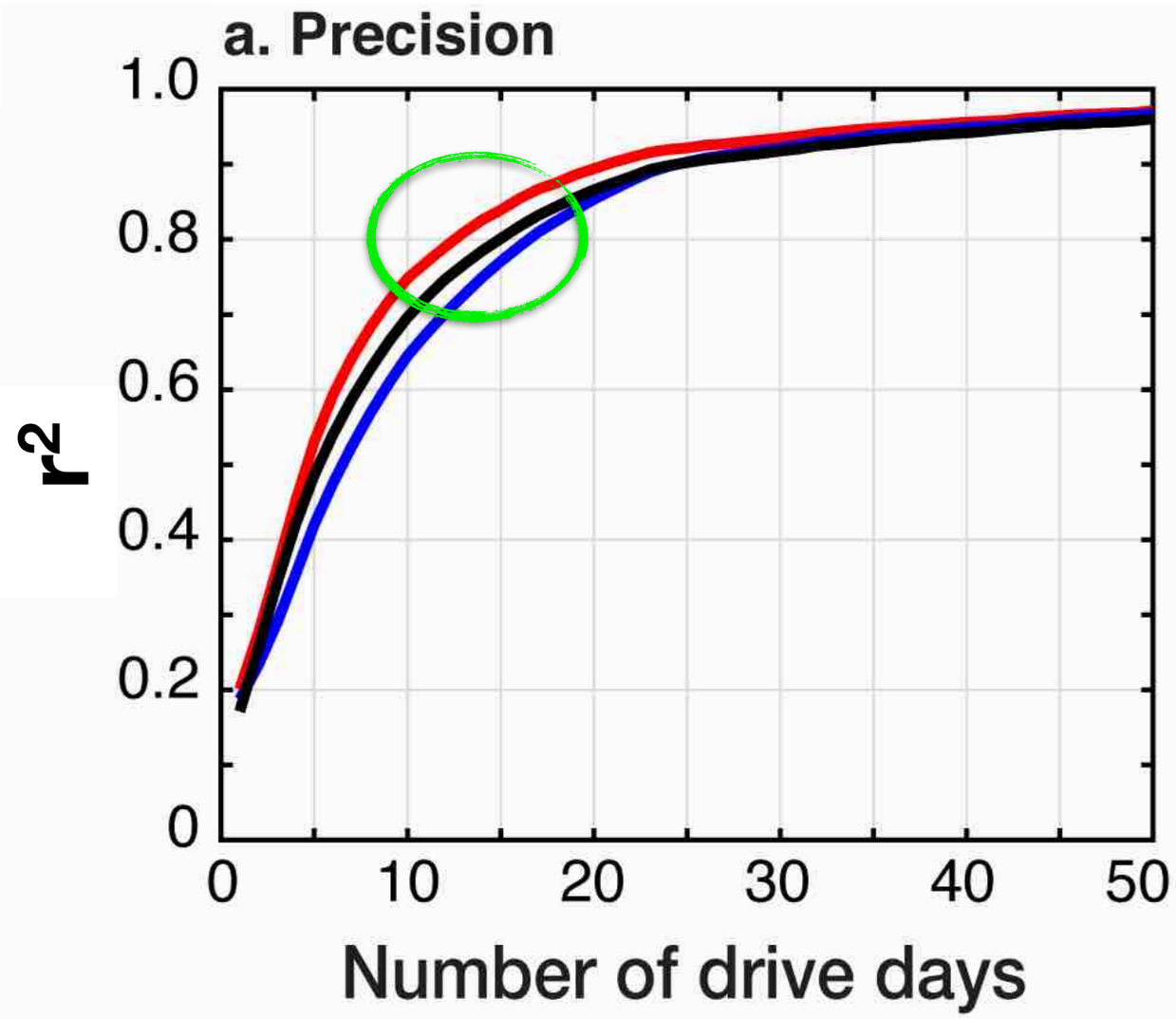
Spatial, temporal patterns have structure related to sources

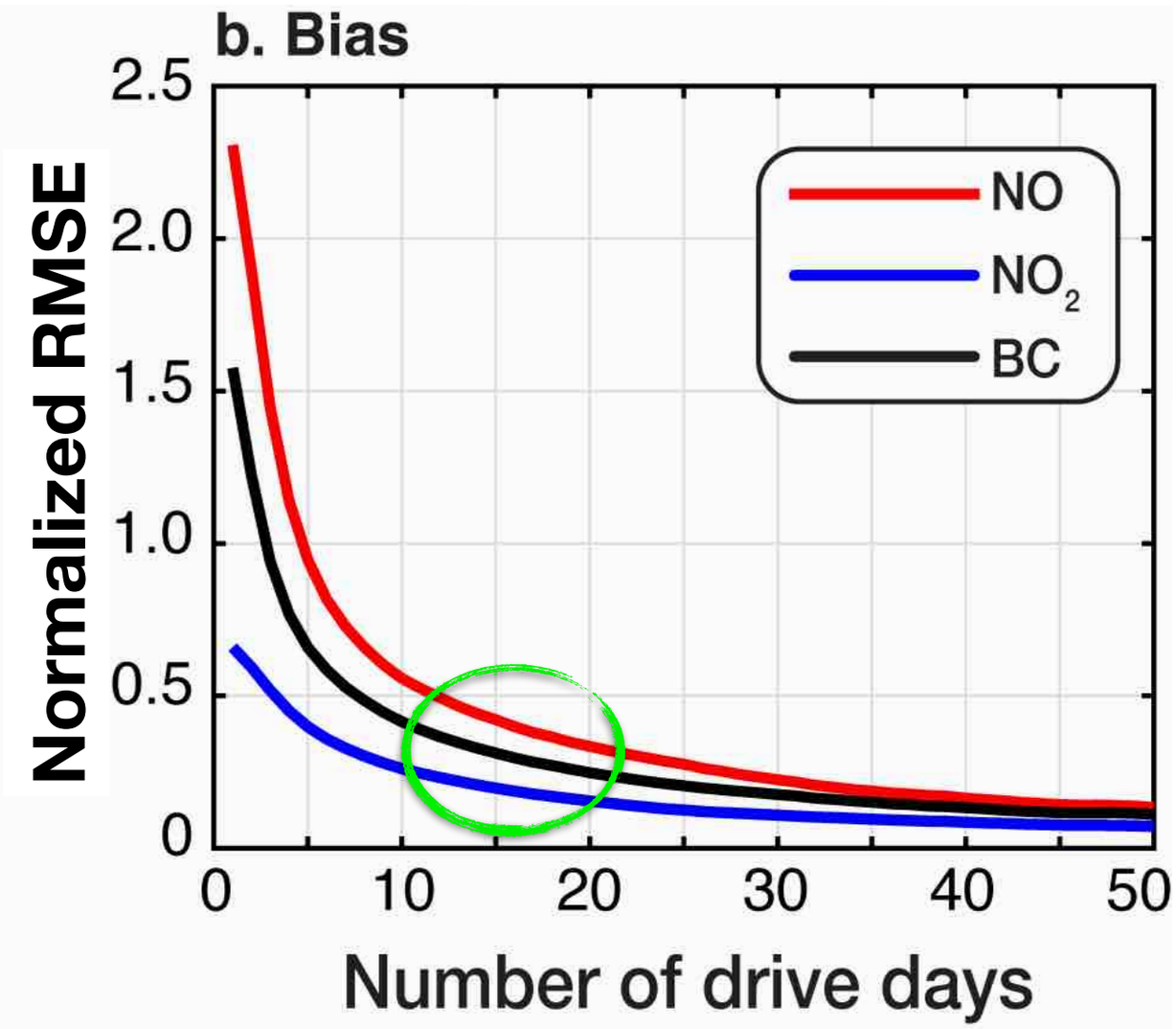
Decay near highways



“Fresh” vs. “aged” mixtures

This method would work with fewer data





10-20 randomly chosen days per road are sufficient to re-create full dataset with high precision, low bias.

Scaling up? Mapping AQ for 111M people

1. Drive 8 h d^{-1} × 200 d y^{-1} = 1600 h y^{-1}

2. Average speed is 25 km h^{-1}

3. One car can drive
40×10^3 km y^{-1}

4. Top 25 US urban areas have 800×10^3 km of roads

5. Need to drive each road 20 times y^{-1}

6. Drive 16×10^6 km y^{-1}

7. Need 400 cars to annually map top 25 US cities

8. Equipment cost is <<$100k/vehicle at scale

Equipment to map air quality for 50% of urban US population costs << $40 M

Application to developing countries (?)

Could this technique work for mapping pollution in developing world?

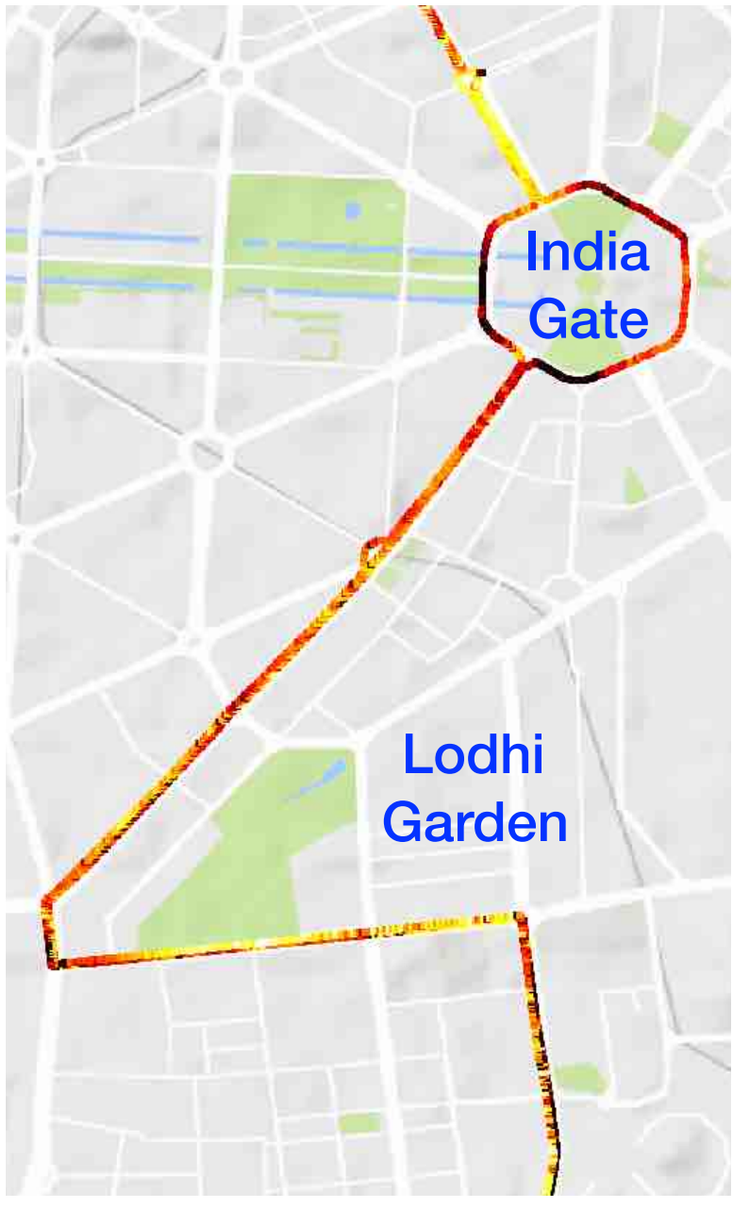
1 Hz particle instruments

Auto-rickshaw based mobile lab, New Delhi, 2010

Repeated mobile monitoring on one route: 60× over 4 months

Pollution levels ~ 10-20× higher, abundant high-emitters

New Delhi, India



Precision @ 10 m : ± 4-11%

Apte et al., *Atmos. Environ.* 45, 4470-4480, 2011

Open questions and future research

- **Nights, weekends:** Can we map stable patterns outside of daytime?
- **Applicability of low-cost sensors:** would this approach work with less precise/accurate instruments?
- **Comparability / complementarity with other approaches:**
  - How do these exposure data differ from LUR, remote sensing, etc?
  - How does the effort-per-data scale?
- Would these data provide value for an **epidemiological study**?

Acknowledgements

Co-authors:

Kyle Messier, UTexas/EDF
Shahzad Gani, UTexas
Melissa Lunden, Aclima, Inc.
Roel Vermeulen, Utrecht University
Julian Marshall, University of Washington
Tom Kirchstetter, LBNL
Michael Brauer, UBC
Chris Portier, EDF
Steve Hamburg, EDF

Aclima, Inc.

Davida Herzl
Okorie Puryear
Alexandra Teste
Jessica Lass
Kim Hunter
Mobile Platform Team

Google Earth Outreach

Karin Tuxen-Bettman
Luc Vincent
Rebecca Moore
Arjun Raman
Carol Owens
Street View Operations Team
Imagery and background maps by Google

Environmental Defense Fund

Ramon Alvarez
Millie Chu Baird
Cassandra Ely

Bay Area AQ Management District

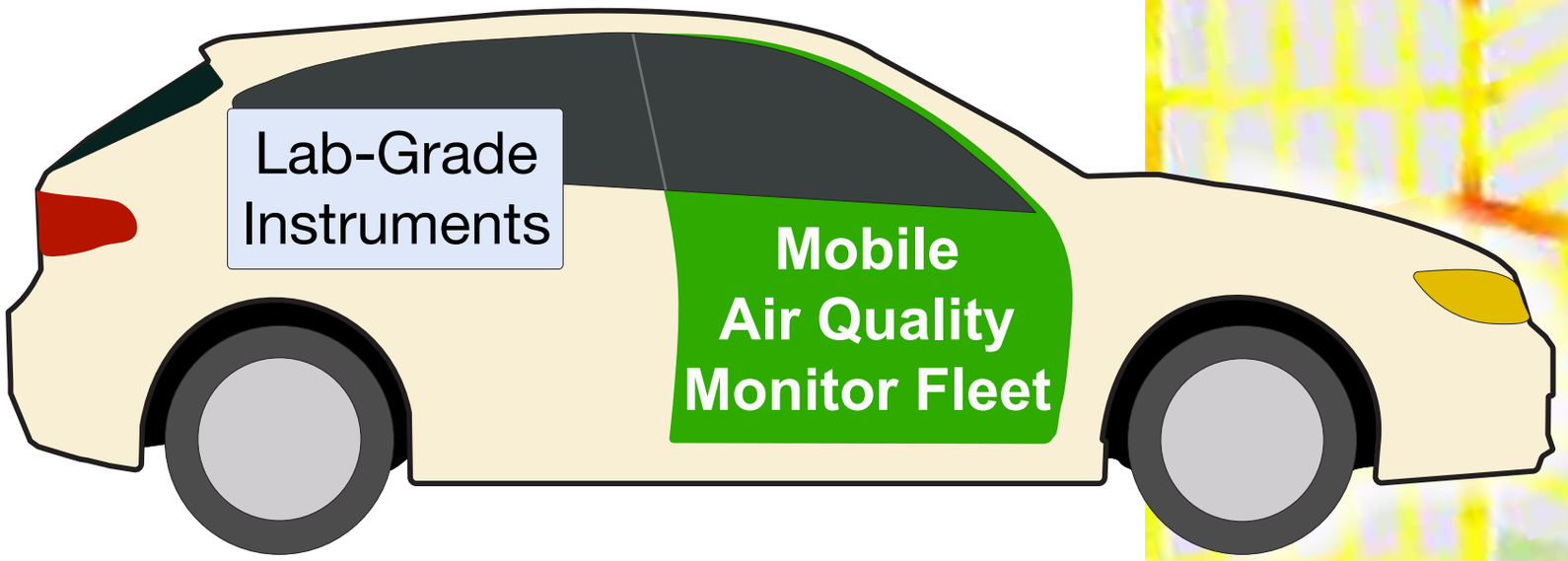
Phil Martien
David Holstius

West Oakland Environmental Indicators Project

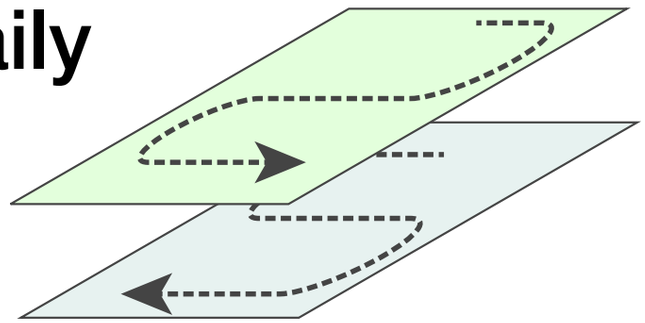
Margaret Gordon
Brian Beveridge

Funding was provided by Signe Ostby and Mark Cook and by a Google Earth Engine Research Award.

Questions?



Repeated daily sampling



3×10^6 data points → QA & reduction algorithms → **Stable 30m air quality maps**