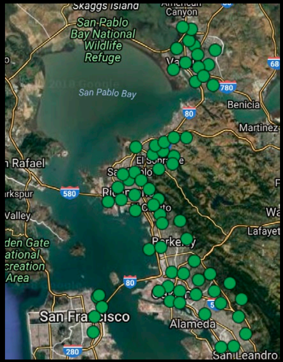
Mapping urban air

Ron Cohen, Professor
Chemistry
Earth and Planetary Science



Catherine Newman

Alexis Shusterman

Jinsol Kim

Kevin Worthington

Alex Turner

Paul Wooldridge

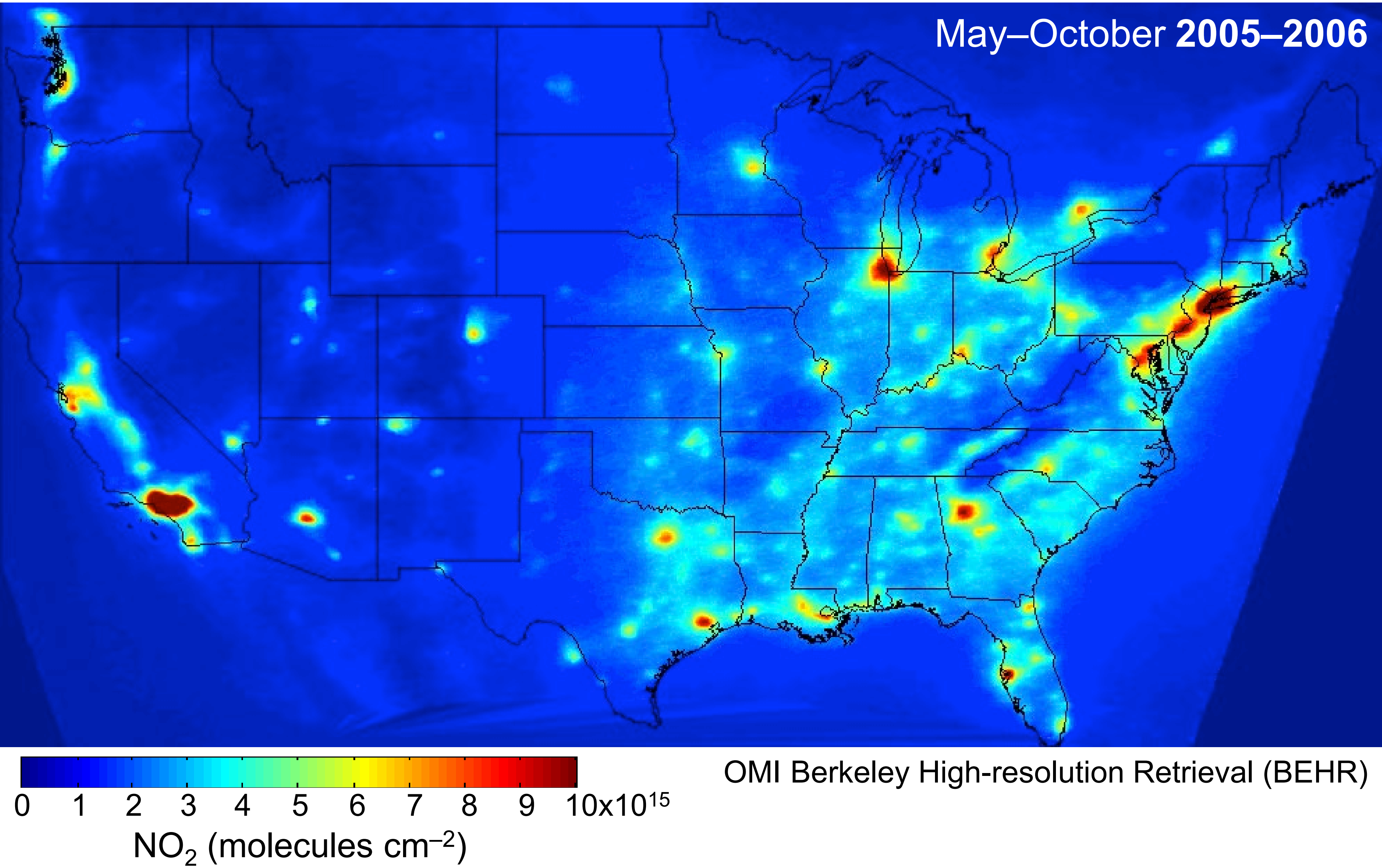
Helen Fitzmaurice

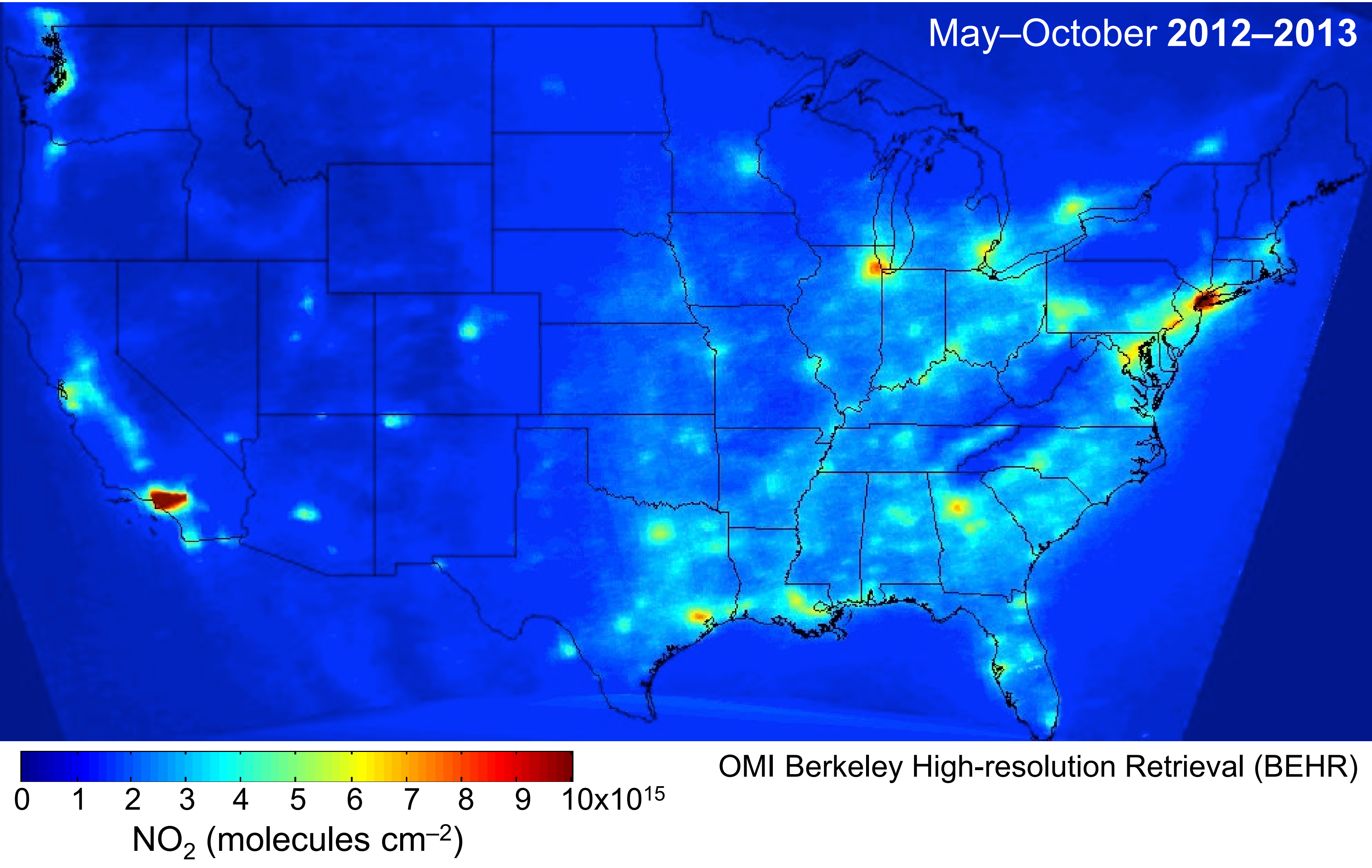
Pietro Vannucci

Naomi Asimow

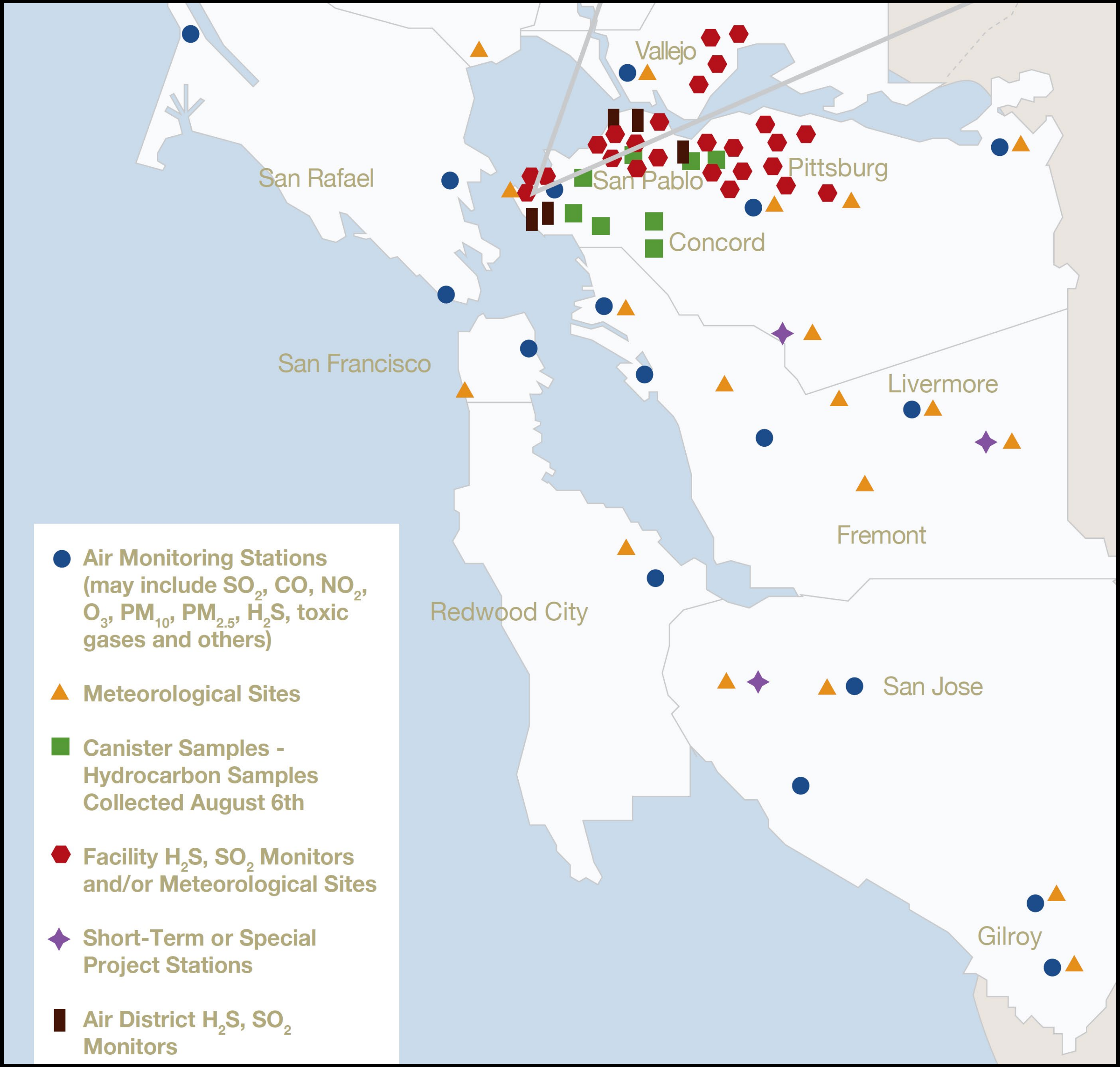
Yishu Zhu

Column of NO_2

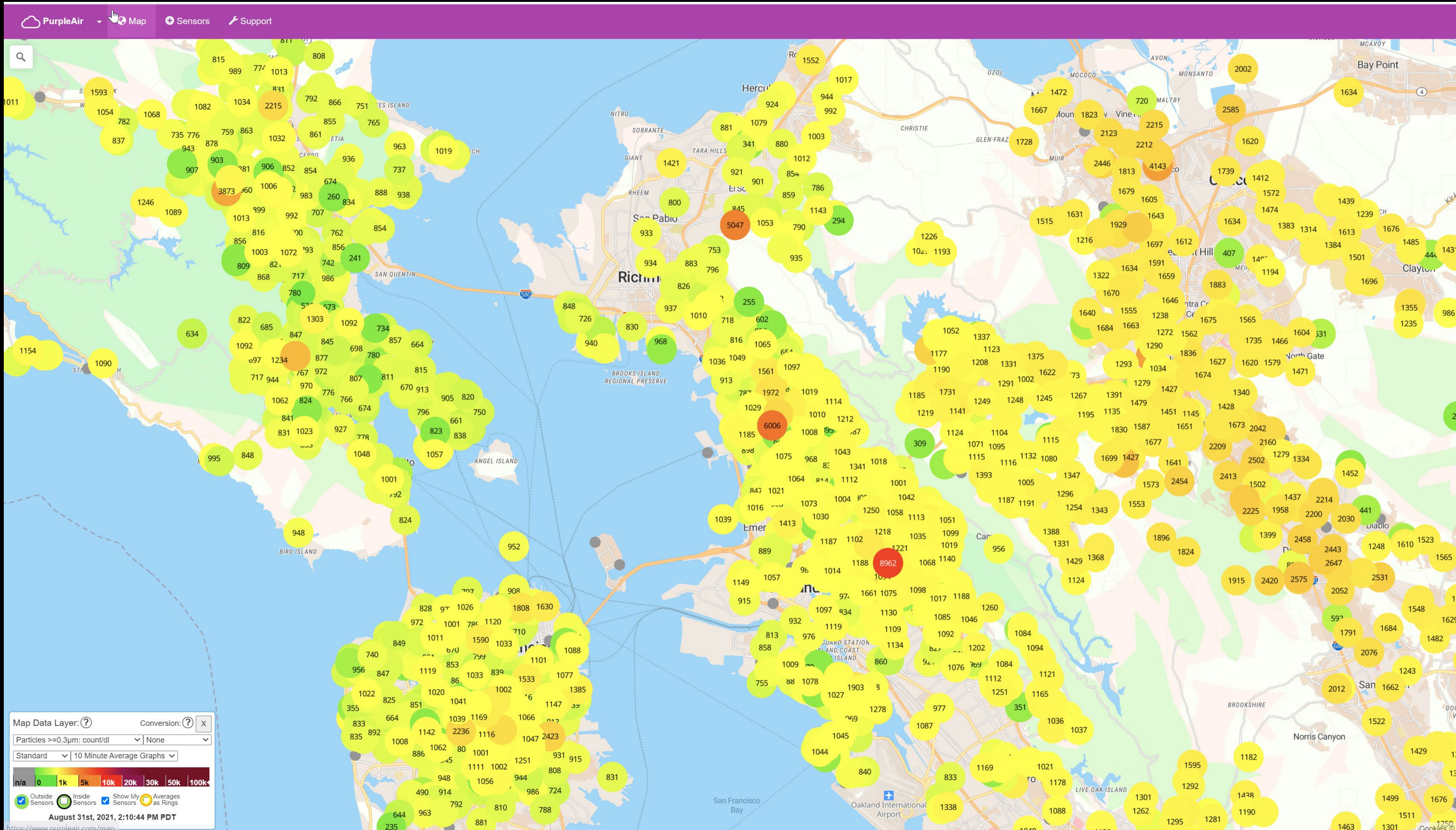



May–October **2012–2013**
0 1 2 3 4 5 6 7 8 9 10x10^15
NO_2 (molecules cm^{-2})
OMI Berkeley High-resolution Retrieval (BEHR)

Standard air quality observations



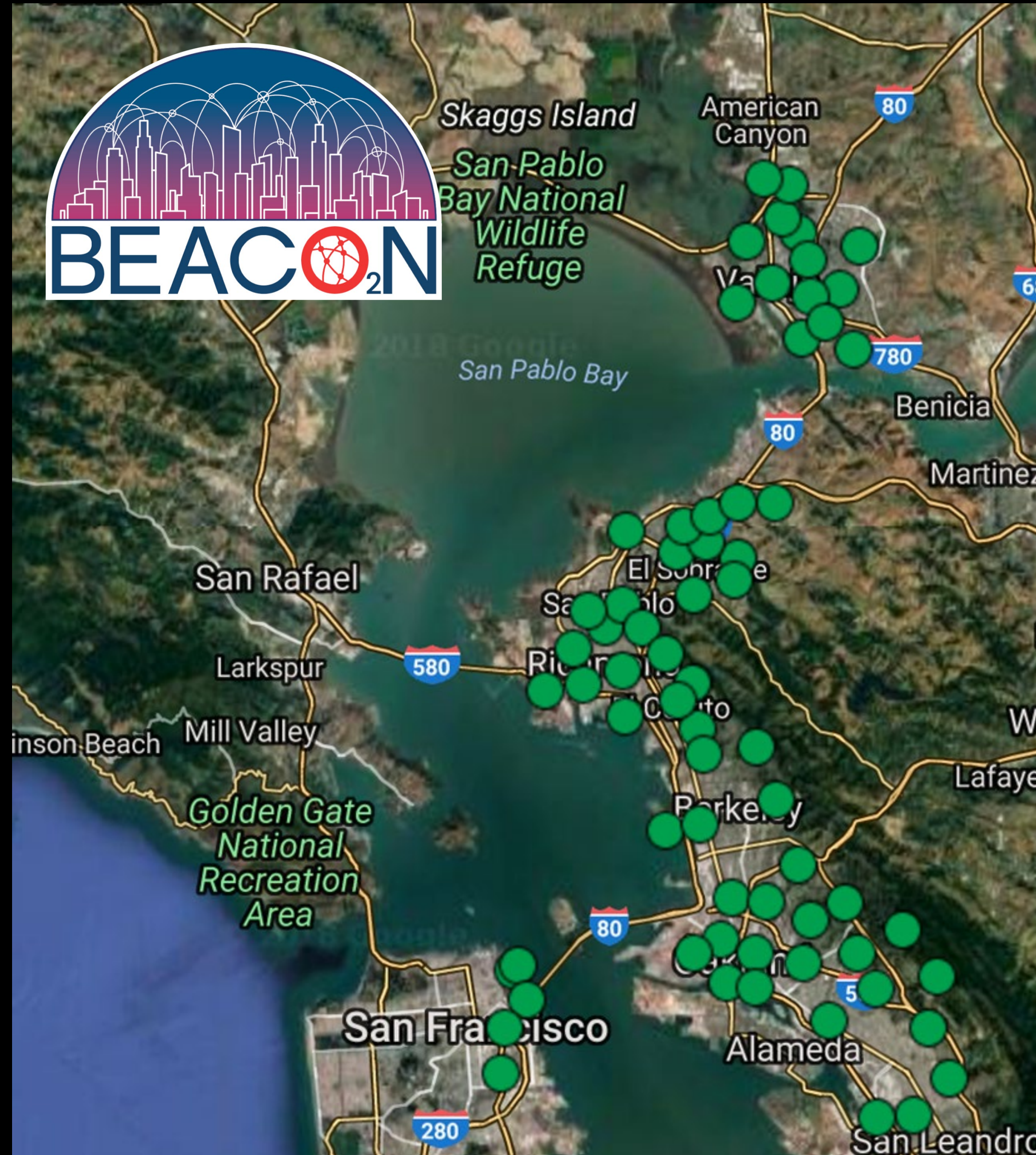
Purple Air network
of particles/dl larger than 300nm



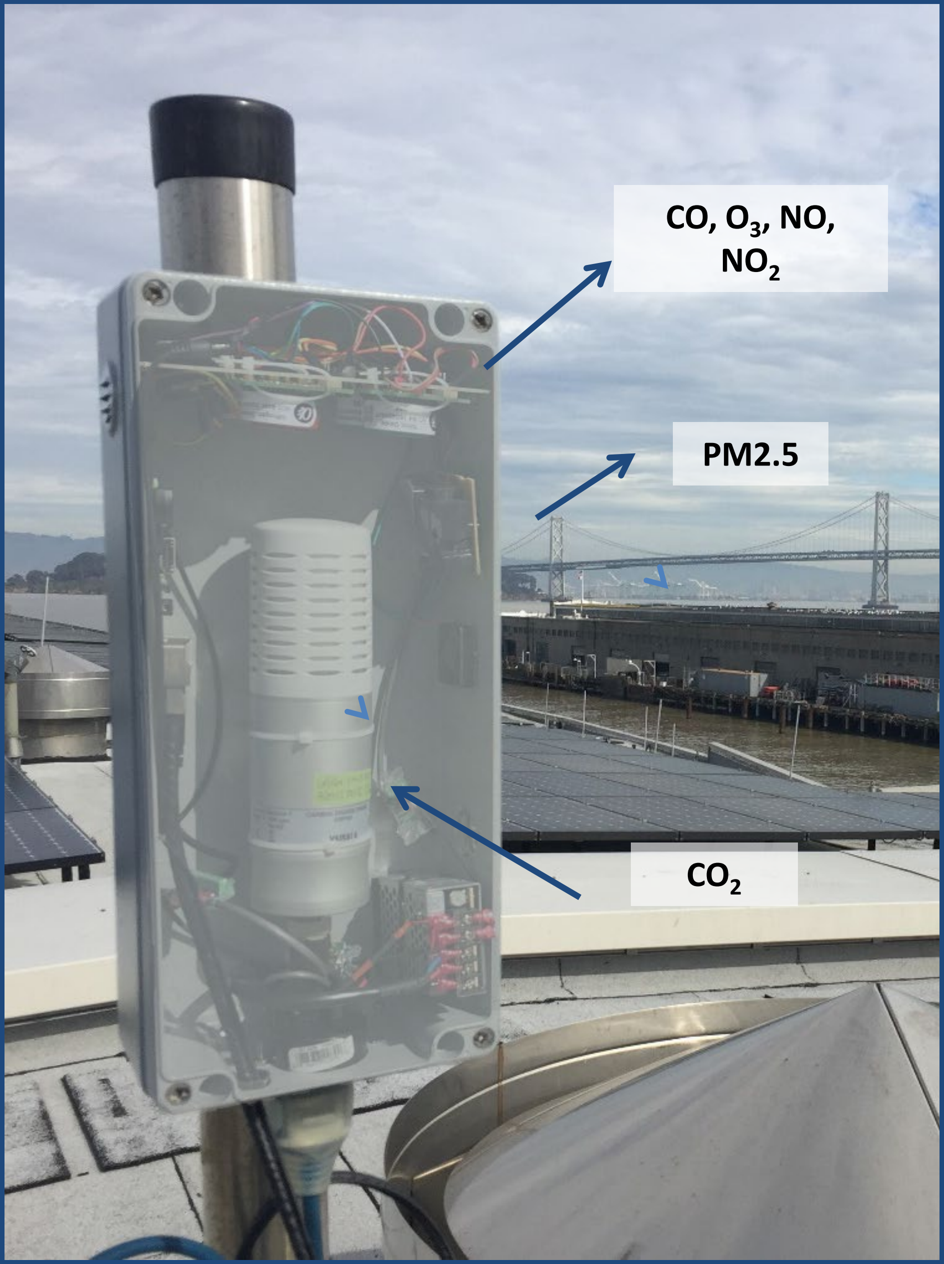
August 31 2021

Berkeley
Environmental
Air Quality and
CO_2
Observation
Network

~2km spacing



http://beacon.berkeley.edu



NO_2, NO, O_3, CO, CO_2, particles

$8500 + shipping; Monthly fee for share of technical support and data management

Maintenance ~10% or less/yr

Note: Hardware costs are small compared to ongoing interpretation.

~20nodes = 1 person year

Our current research on instrumentation is aimed at lowering the personnel costs.

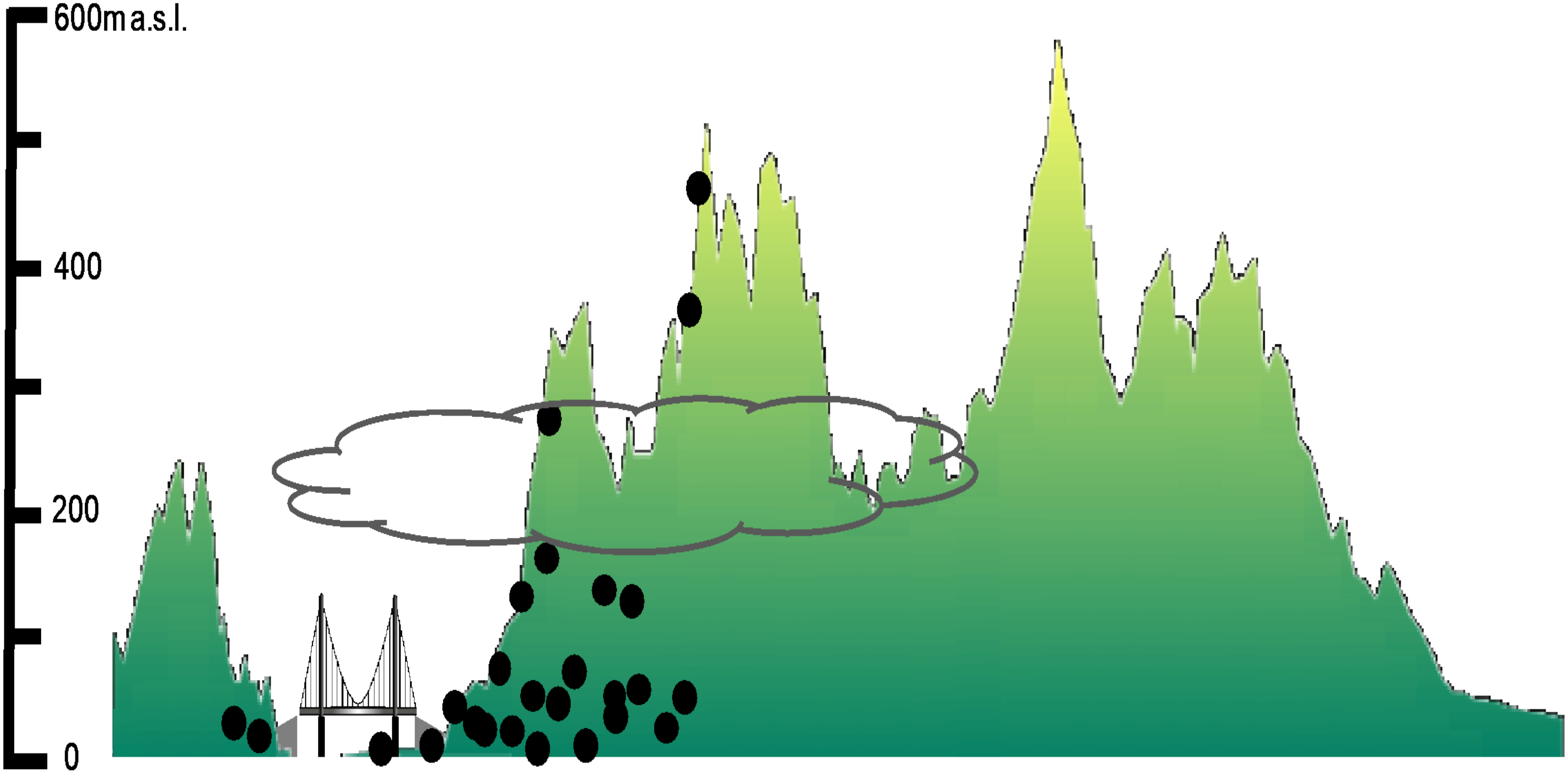
A. Shusterman, et al., ACP. 2016

J. Kim, et al. AMT, 2018

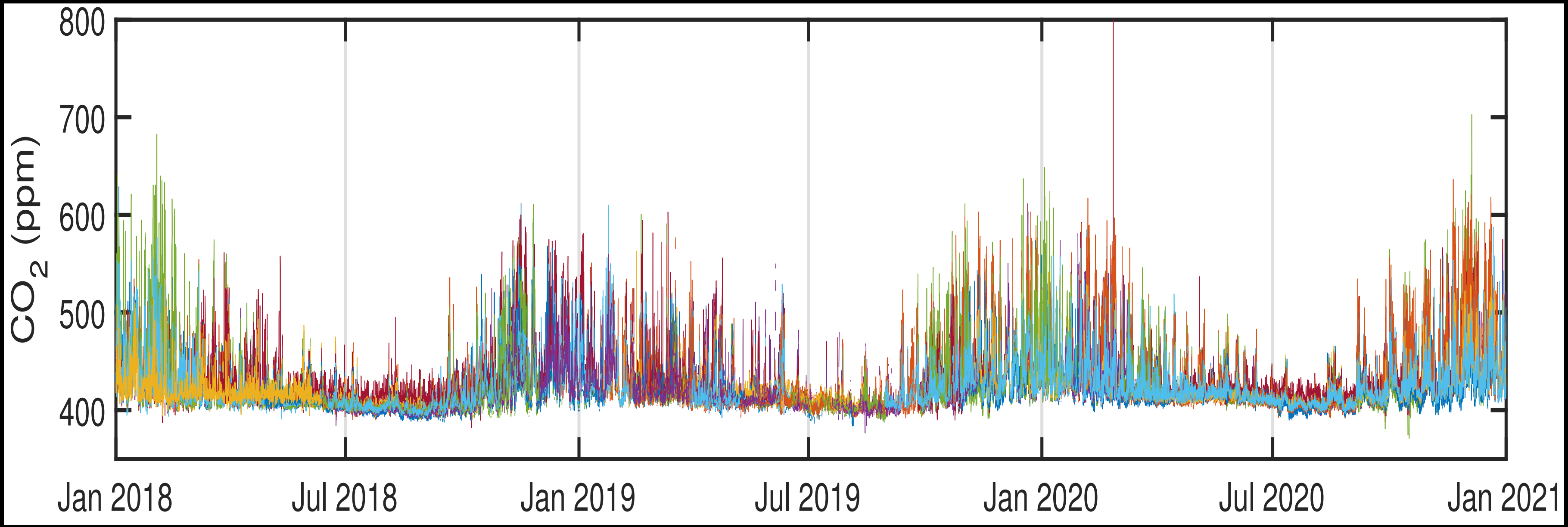
E.R. Delaria et al. ACP. 2021

BEACO$_2$N: 2.5m – 130m AGL

BEACO$_2$N

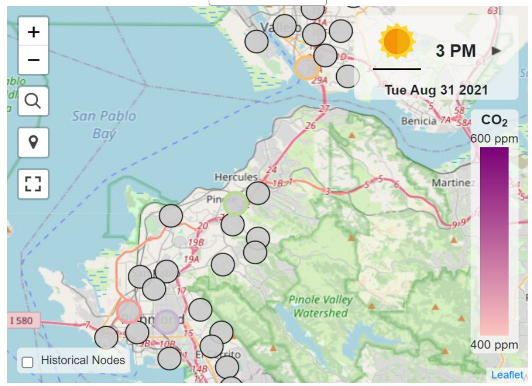


What makes BEACO$_2$N unique is the combination of CO$_2$ and AQ. This brings together siloed research (AQ, GHGs, Climate, EJ) and policy communities (NGOs, cities, regions, national government) that should be working more closely together.



climate change, and reports back to this site where the collected data is publicly available for viewing and download. The nodes also collect data on nitrogen oxides, ozone, carbon monoxide, and particulate matter which are indicators for the overall air quality of an area, and may be useful for tracing the origins of CO_2 emissions. CO_2, CO, and aerosol data are available for download via this site. Data for other species is not yet ready for public viewing, but will be added to the site soon.

Select Area



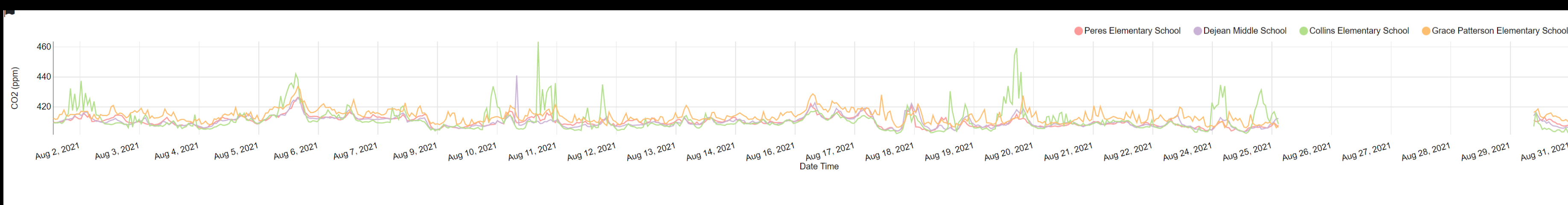
× Peres Elementary School
× Dejean Middle School
× Collins Elementary School
× Grace Patterson Elementary School

Date Range: 2021-08-01 15:00:00 to 2021-08-31 15:00:00 CO2

Real-time

Data is posted and available to the public as it comes in.

Open data, calibration and interpretation.



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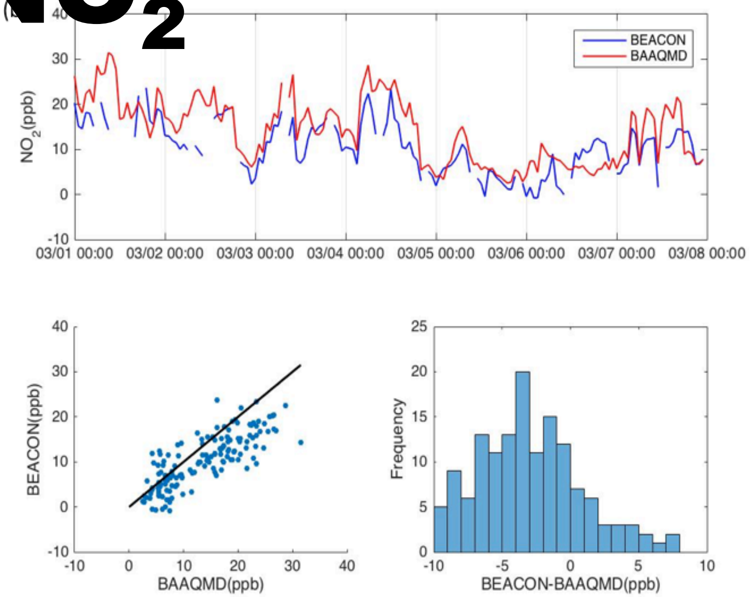
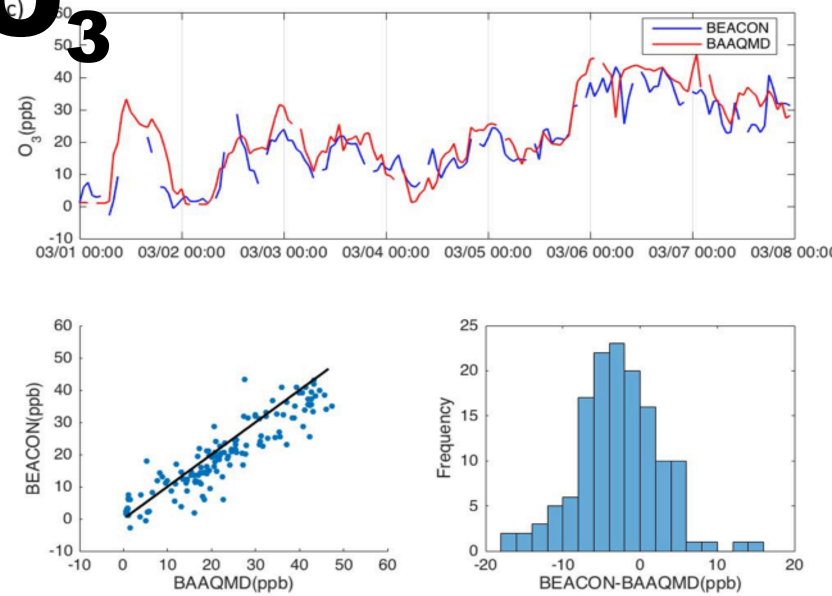
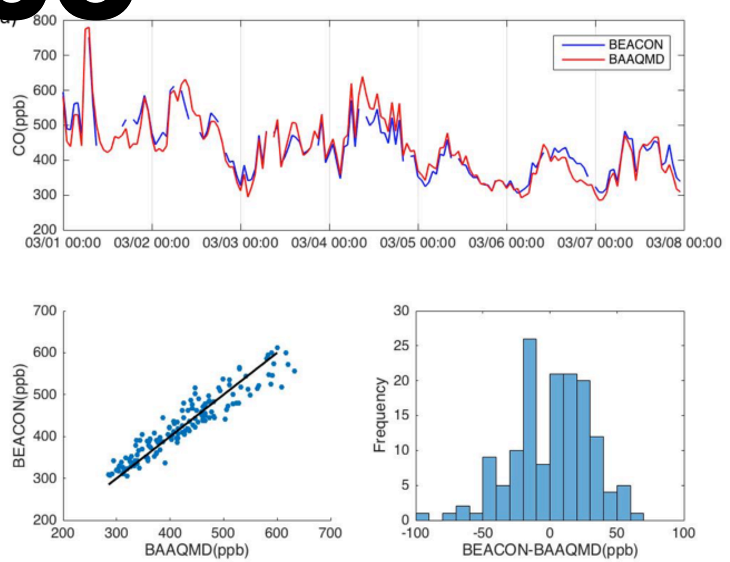
NO_2



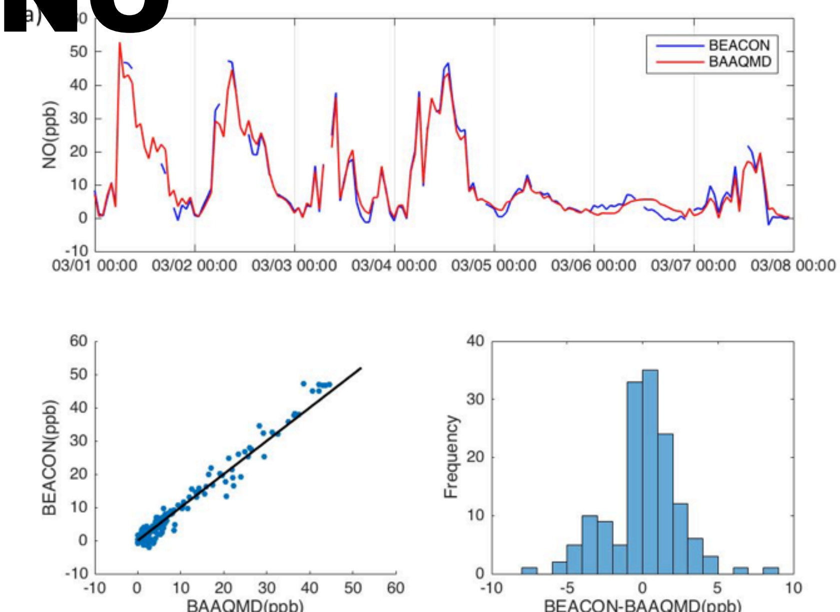
O_3



CO

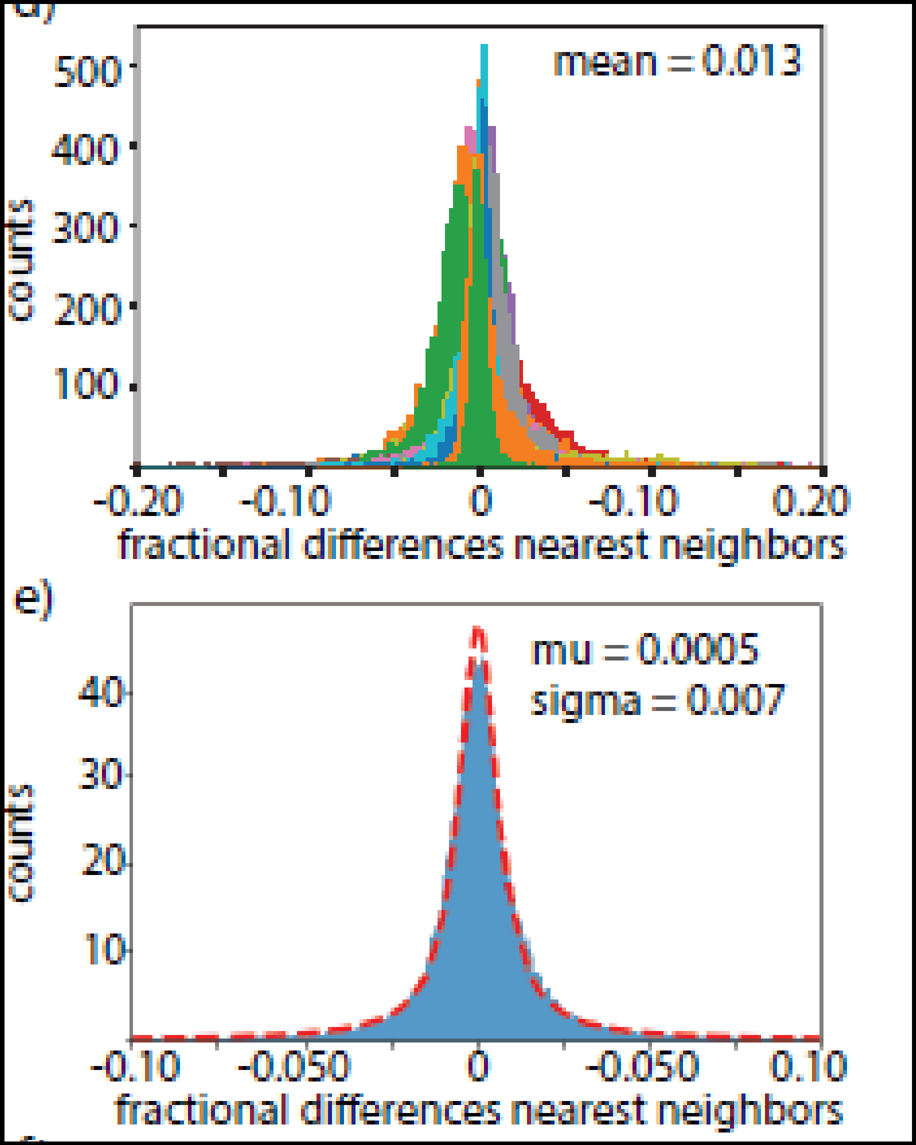


NO



Blue $BEACO_2N$ Red Independent

Evaluation of CO_2 Calibration



Delaria, et al. 2021

Advantages of dense networks

Spatial density; mapping; e.g. 1 obs/2 sq km

many, many small footprints

large numbers; overcome biases of any individual instrument/site ~(100 1ppm uncertainty sensors equivalent to 0.1 ppm in regional mean) but also yield maps.

hypothesis that large numbers allow statistics to overwhelm many other kinds of bias, error and uncertainty in sampling and interpretation

California Greenhouse Gas policy 1990 reference point

- **2006**

Executive Order S-3-05 – reduce GHGs **80% by 2050**.

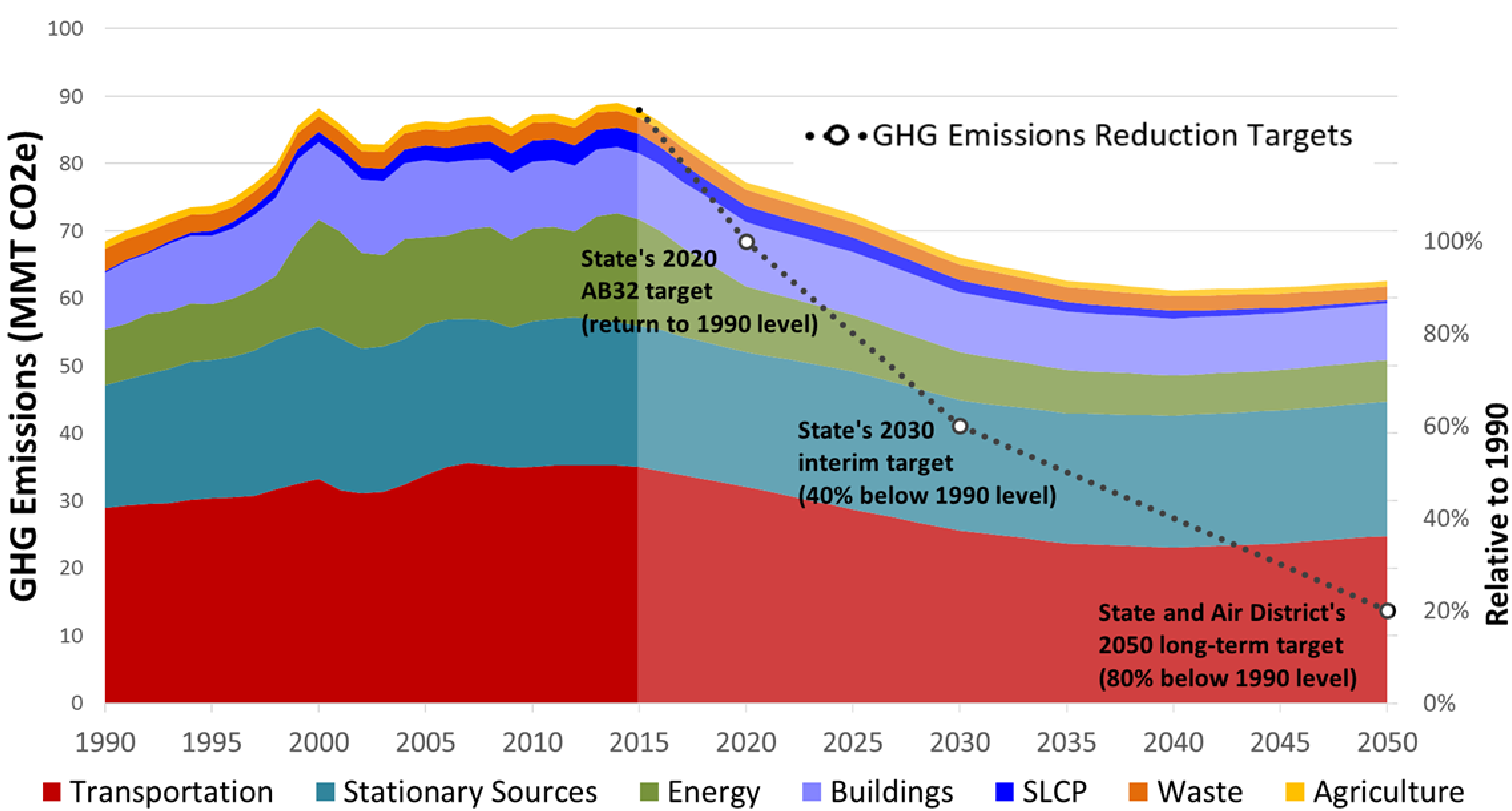
Assembly Bill, AB 32 **– to 1990 levels by year 2020.**

- **2015/2016**

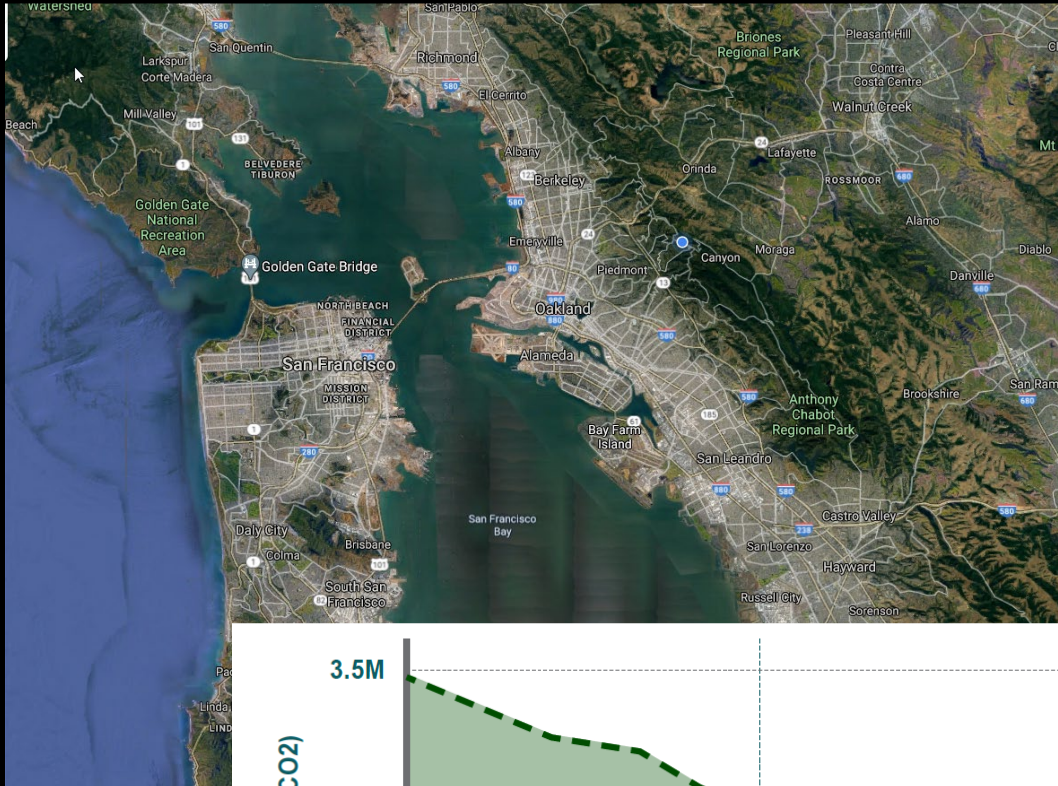
Executive Order B-30-15, Senate Bill, SB 32 (2016) – **40% by 2030**

- 50% of electricity from renewable sources by 2030
- 50% reduction in petroleum use in cars and trucks by 2030.
- Double the energy efficiency savings in end-use electricity and natural gas at existing buildings by 2030.

90% CO_2, 5% CH_4

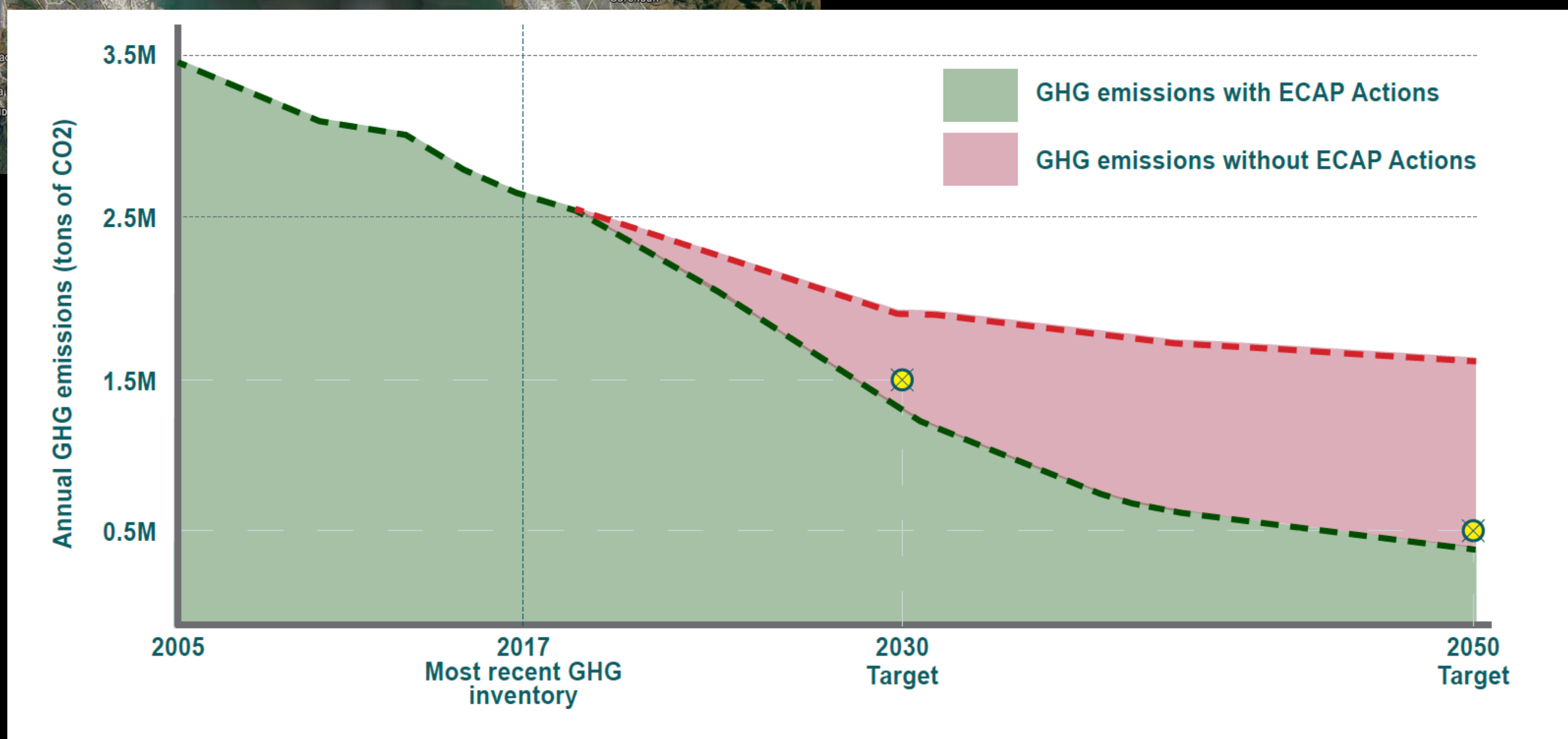


GHG Emissions (MMT CO2e)
100
90
80
70
60
50
40
30
20
10
0
GHG Emissions Reduction Targets
State's 2020
AB32 target
(return to 1990 level)
State's 2030
interim target
(40% below 1990 level)
State and Air District's
2050 long-term target
(80% below 1990 level)
100%
80%
60%
40%
20%
0%
Relative to 1990
1990
1995
2000
2005
2010
2015
2020
2025
2030
2035
2040
2045
2050
Transportation
Stationary Sources
Energy
Buildings
SLCP
Waste
Agriculture

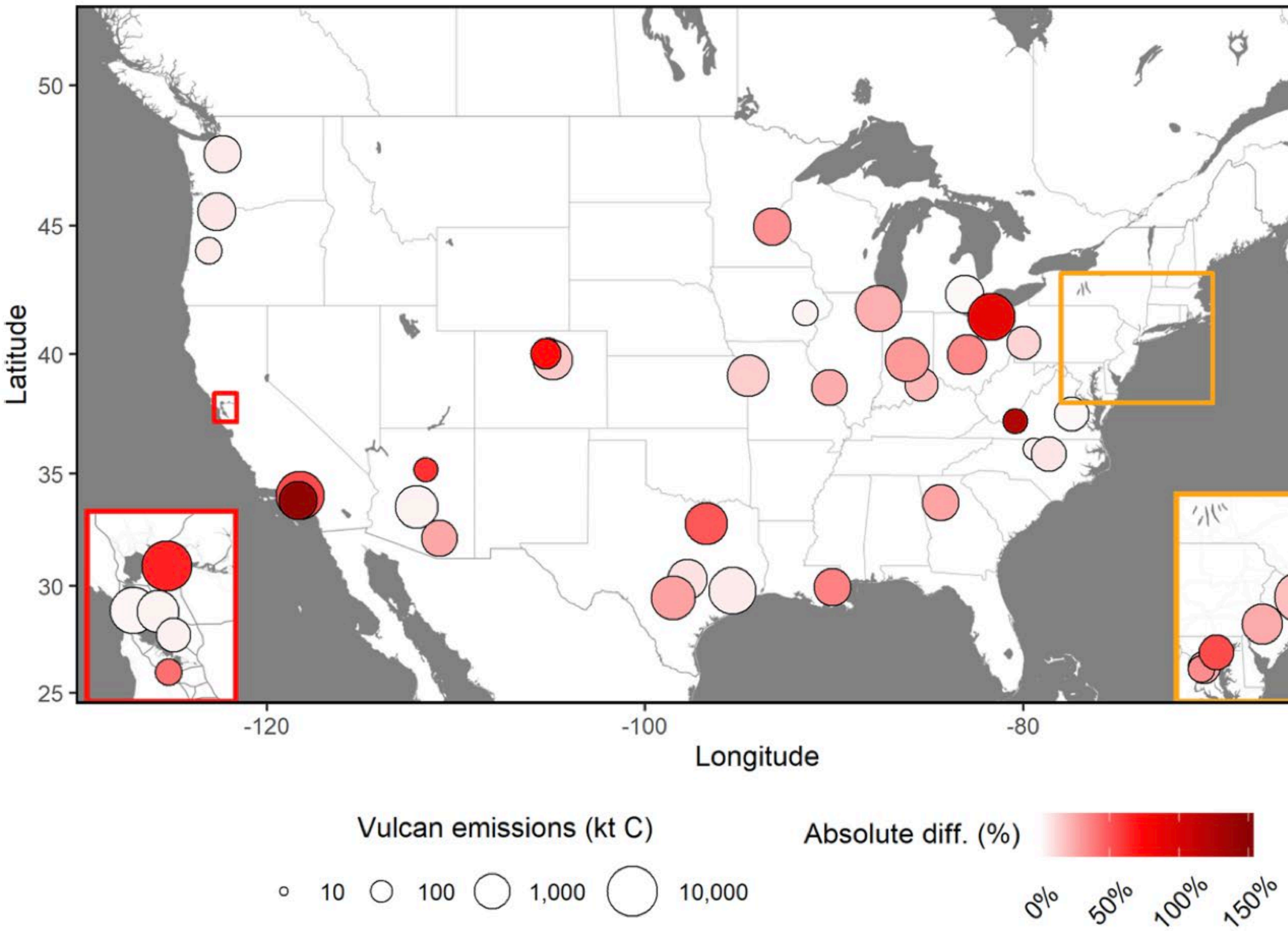


Oakland

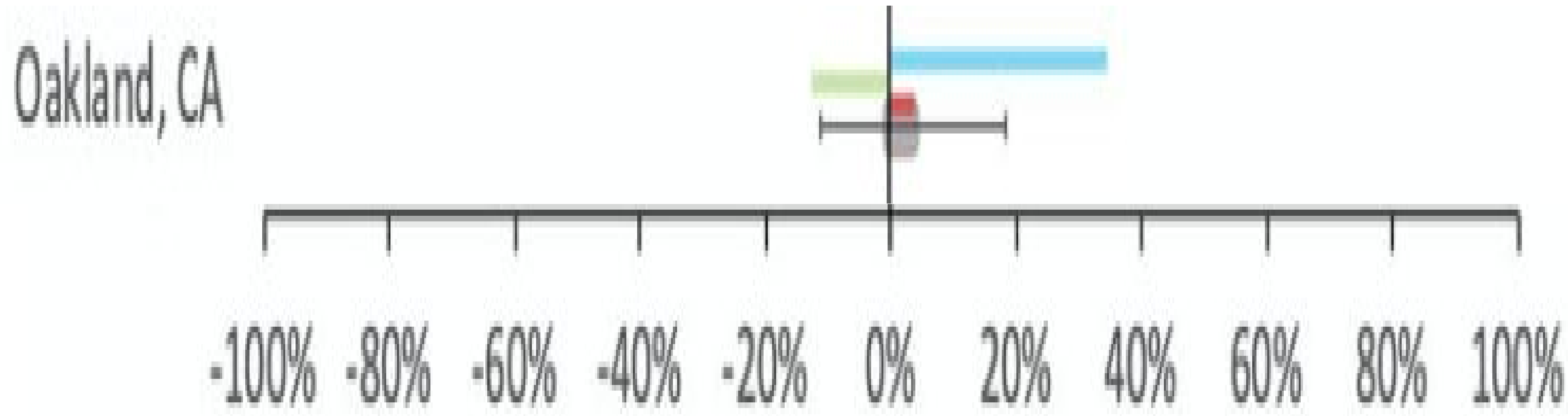
City 435,000 people
Region 8.7 million



People of goodwill are challenged to develop a consistent approach to describing emissions



(Gurney, et al. 2021)



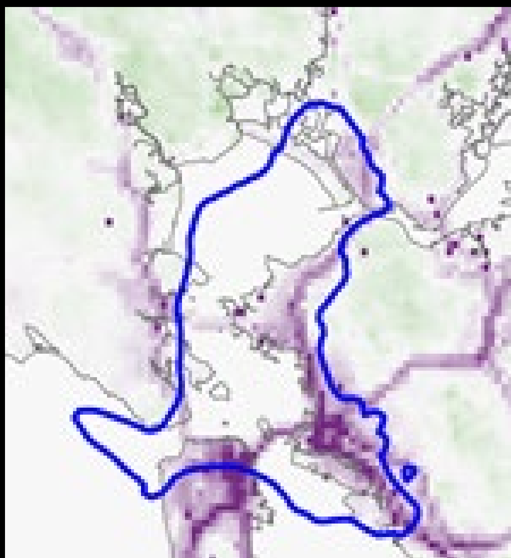
Blue: off-road transport
Green: stationary sources
Grey: Total

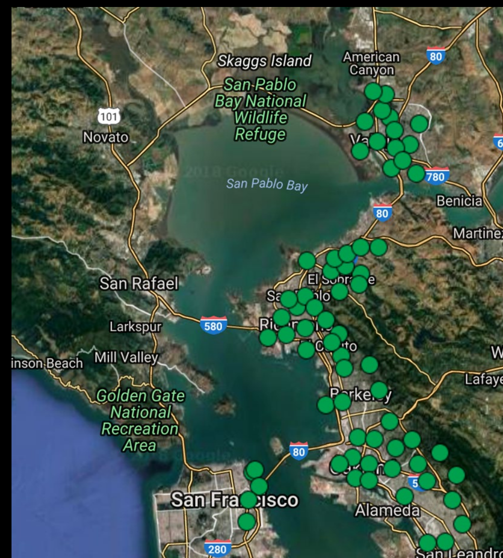
(Gurney, NAU 2021)

What can we learn from dense mapping of air?

optimization of an inventory through
inverse modeling—e.g. Turner et al. GRL 2020

3 steps in a cycle of observation driven understanding of emissions





$$\hat{\mathbf{x}} = \mathbf{x_a} + (\mathbf{HB})^T \left(\mathbf{HBH}^T + \mathbf{R}\right)^{-1} (\mathbf{y} - \mathbf{Hx_a})$$

Predictions/ hypotheses

economic, social, and weather

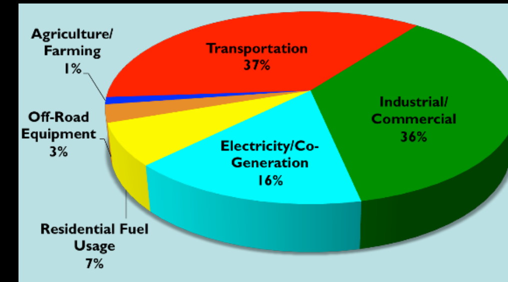
Observations

sensor networks

Synthesis/iterative improvement

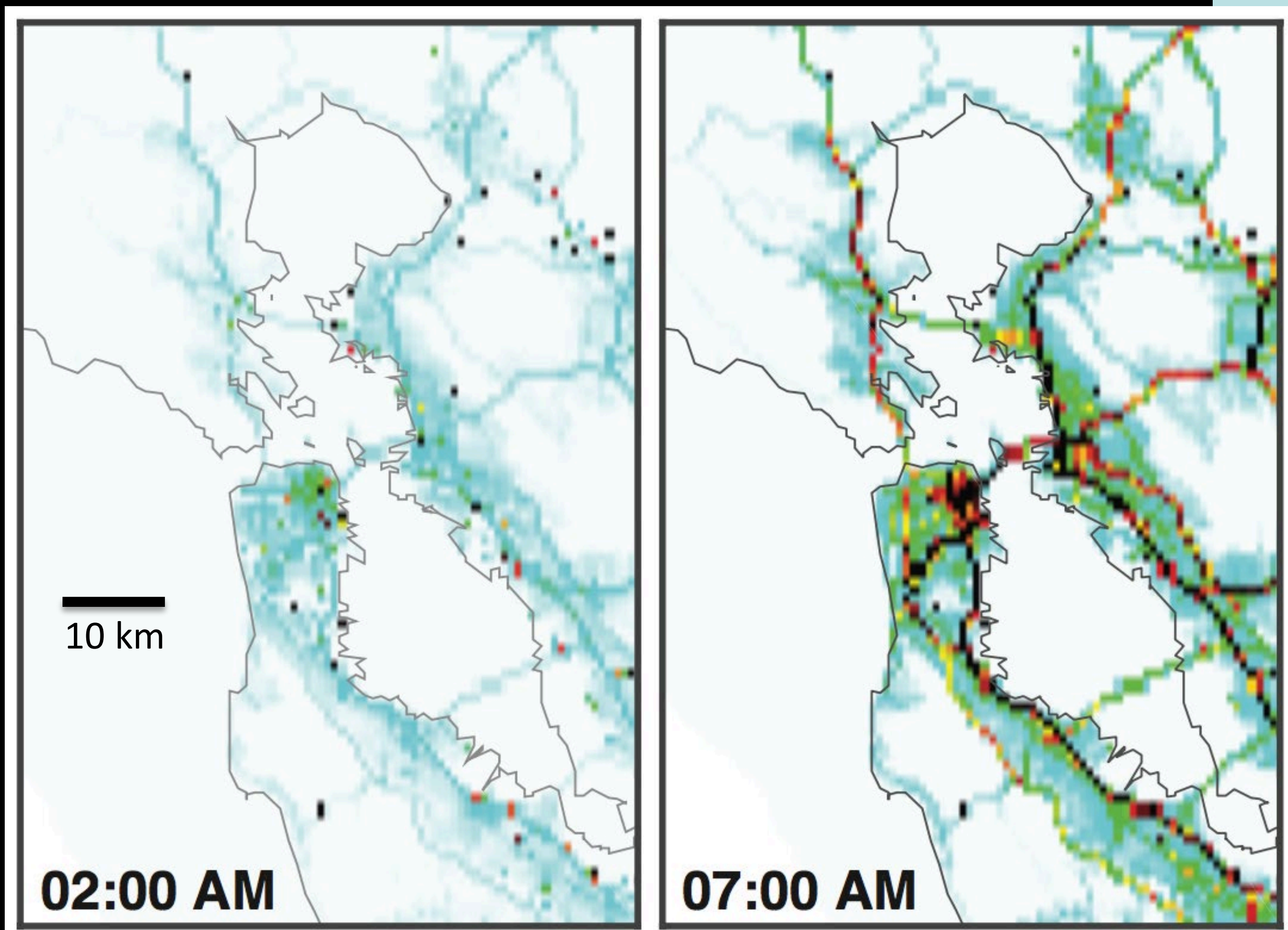
inverse model

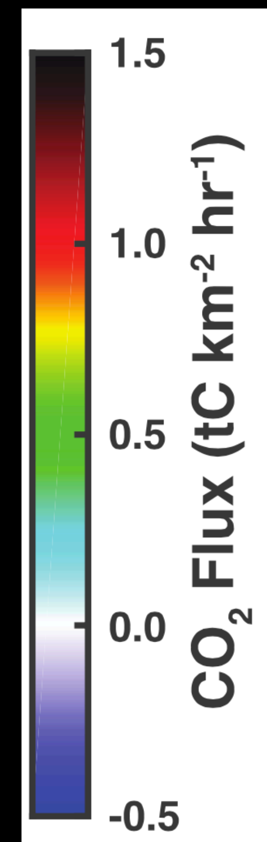
CO_2 emissions



Industry

Vehicles





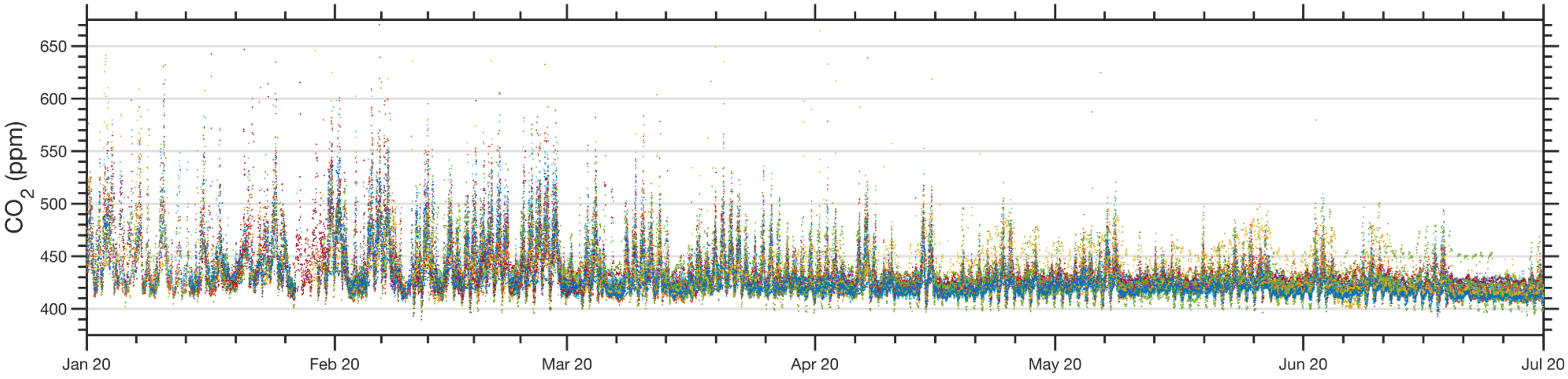
Turner et al., ACP 2016

Combine with a weather model

CO_2 concentration, 1 km grid; 3 days

Observations

$$\hat{\mathbf{x}} = \mathbf{x_a} + (\mathbf{HB})^T \left(\mathbf{HBH}^T + \mathbf{R}\right)^{-1} (\underline{\mathbf{y}} - \mathbf{Hx_a})$$



$$\hat{\mathbf{x}} = \mathbf{x_a} + (\mathbf{HB})^T \left(\mathbf{HBH}^T + \mathbf{R}\right)^{-1} (\mathbf{y} - \mathbf{Hx_a})$$

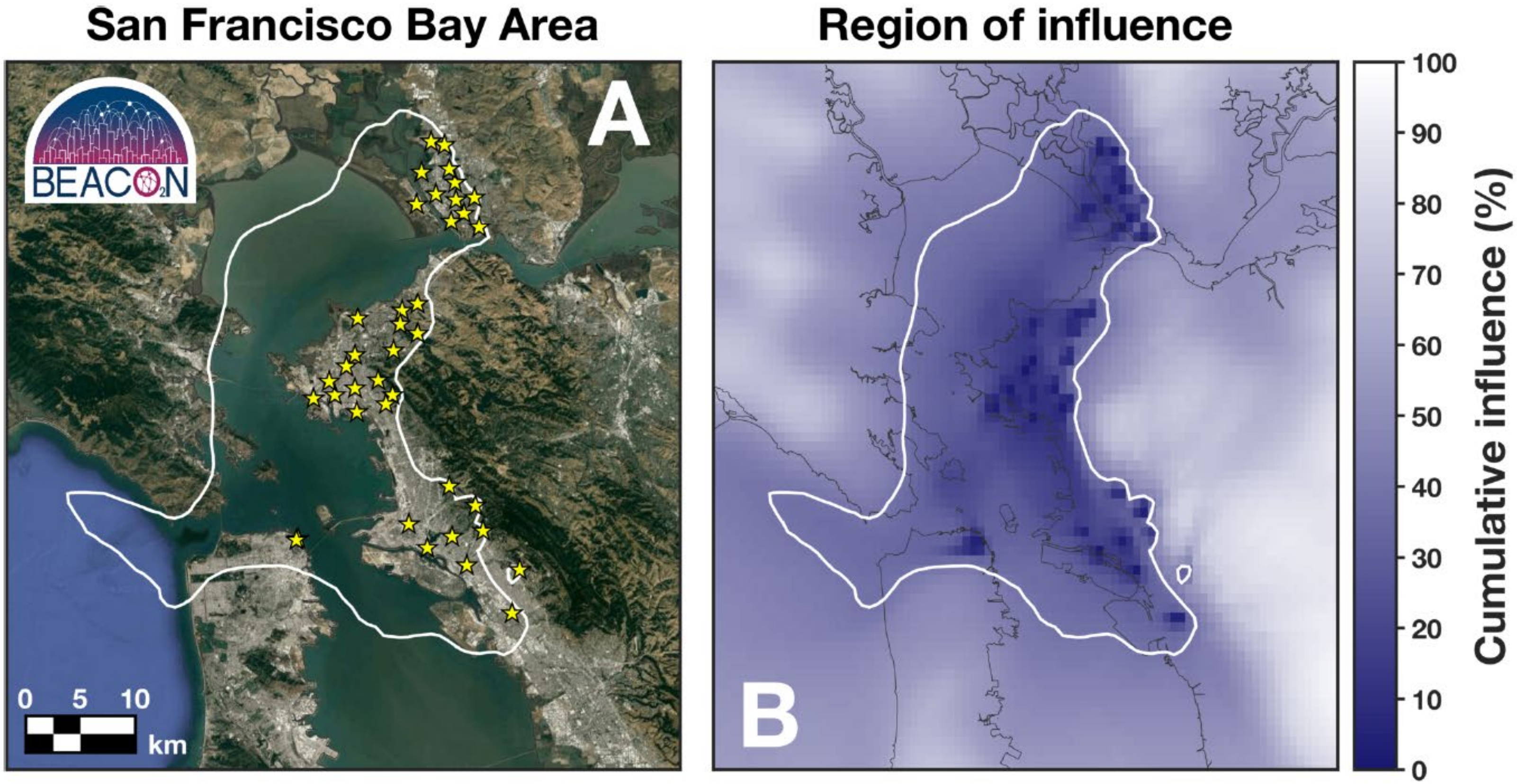
Model-data mismatch error covariance matrix

$$\hat{\mathbf{x}} = \mathbf{x_a} + (\mathbf{HB})^T \left(\mathbf{HBH}^T + \underline{\mathbf{R}}\right)^{-1} (\mathbf{y} - \mathbf{Hx_a})$$

$$\mathbf{R} = \underbrace{\mathbf{R}_I}_{\text{instrument error}} + \underbrace{\mathbf{R}_B}_{\text{background error}} + \underbrace{\mathbf{R}_M}_{\text{model error}}$$

Footprint matrix

$$\hat{\mathbf{x}} = \mathbf{x_a} + (\underline{\mathbf{H}}\mathbf{B})^T \left(\underline{\mathbf{H}}\mathbf{B}\underline{\mathbf{H}}^T + \mathbf{R}\right)^{-1} (\mathbf{y} - \mathbf{H}\mathbf{x_a})$$



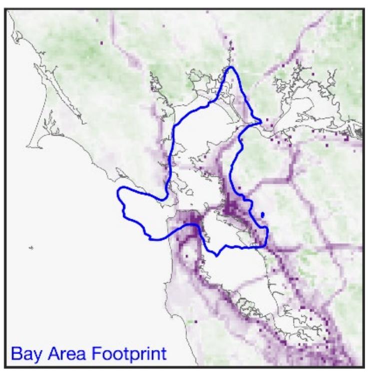
NOAA HRRR meteorology, 72 hour back trajectories with 1000 particles (STILT)

Defining the system of equations

Goal: Estimate hourly fluxes at 900-m for 15 days

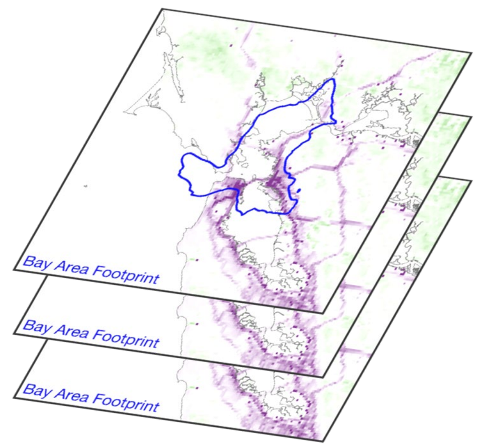
- **Problem setup** (“small domain”):
  - Horizontal grid is $n_x \times n_y$ where n_x = 157 and n_y = 121
  - 15 days of hourly fluxes: n_t = 360
- Reshape each timestep into a vector ($n_x n_y$ = 18,997 spatial elements)
- “Stack” the timesteps ($m = n_x n_y n_t$ = 6,338,920 parameters): **55 Mb***!

$\mathbf{x}_1 =$



$=$

$\mathbf{x} =$



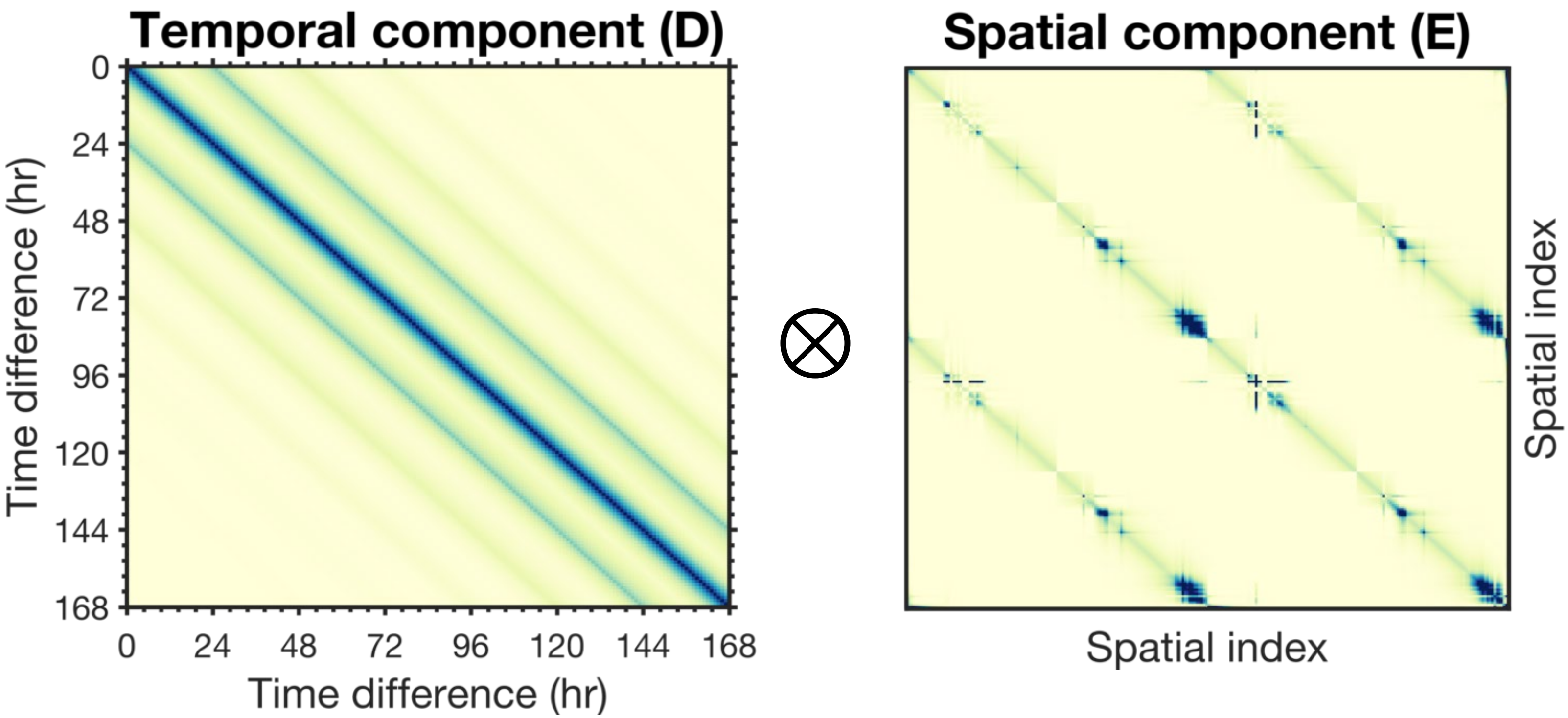
$$= \begin{pmatrix} \begin{pmatrix} \vdots \\ \mathbf{x}_1 \\ \vdots \end{pmatrix} \\ \vdots \\ \begin{pmatrix} \vdots \\ \mathbf{x}_{360} \\ \vdots \end{pmatrix} \end{pmatrix}$$

- Prior error covariance matrix is $[m \times m]$ $\mathbf{4.7 \times 10^{13}}$ elements (**374 Tb***!)

**Assuming double precision: 8 bytes per element*

prior error covariance matrix…

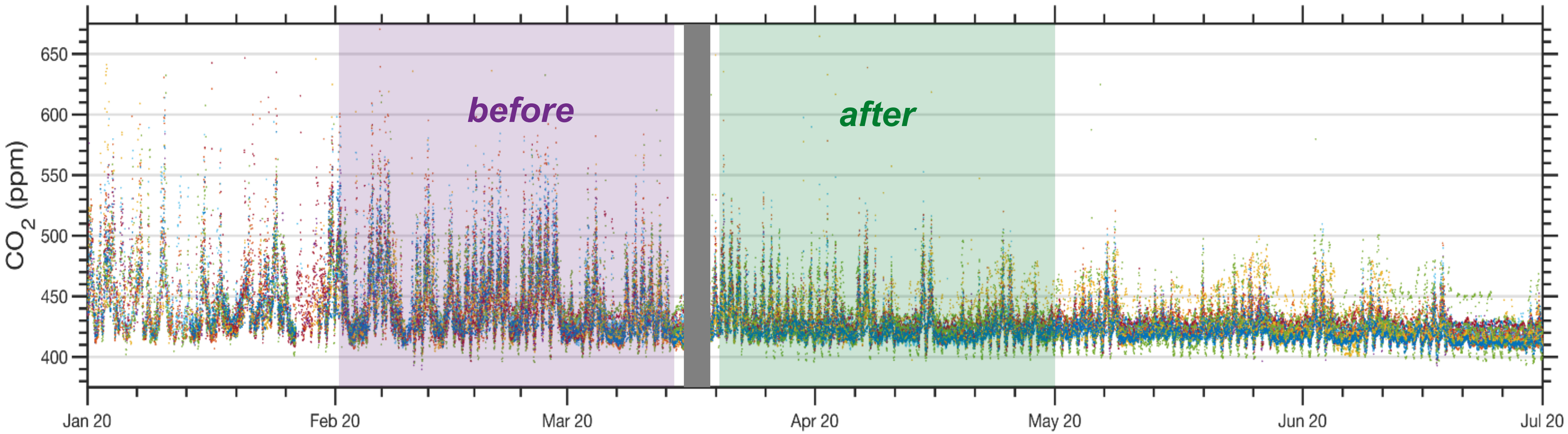
- Can describe as a Kronecker product (⊗) of two sub-matrices



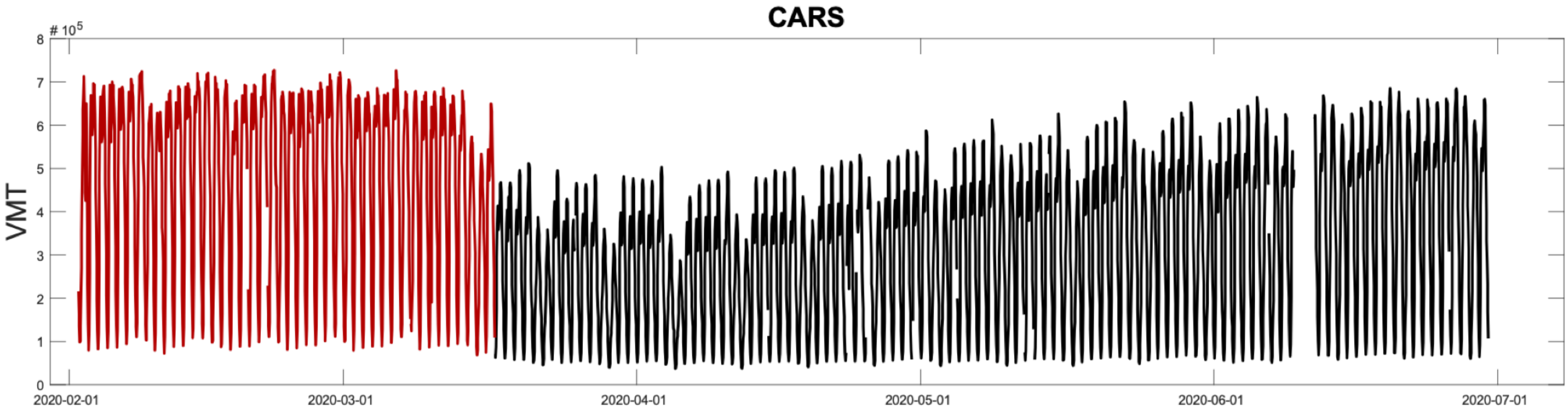
How much did CO_2 emissions drop in the early phase of the COVID-19 shelter-in-place and why?

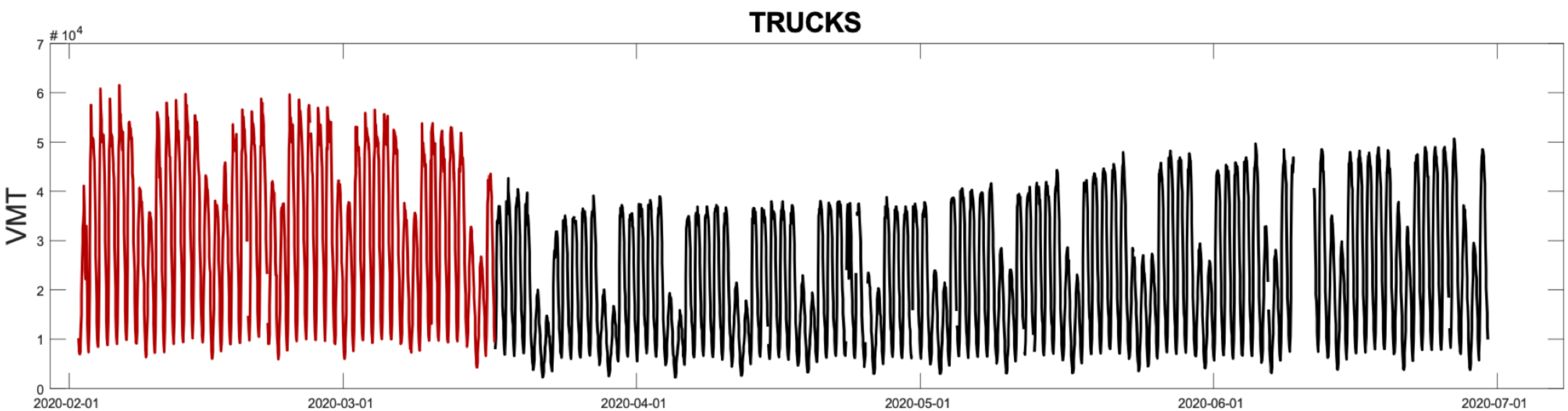
Turner, et al., Geophys. Res. Lett. doi.org/10.1029/2020GL09003, 2020

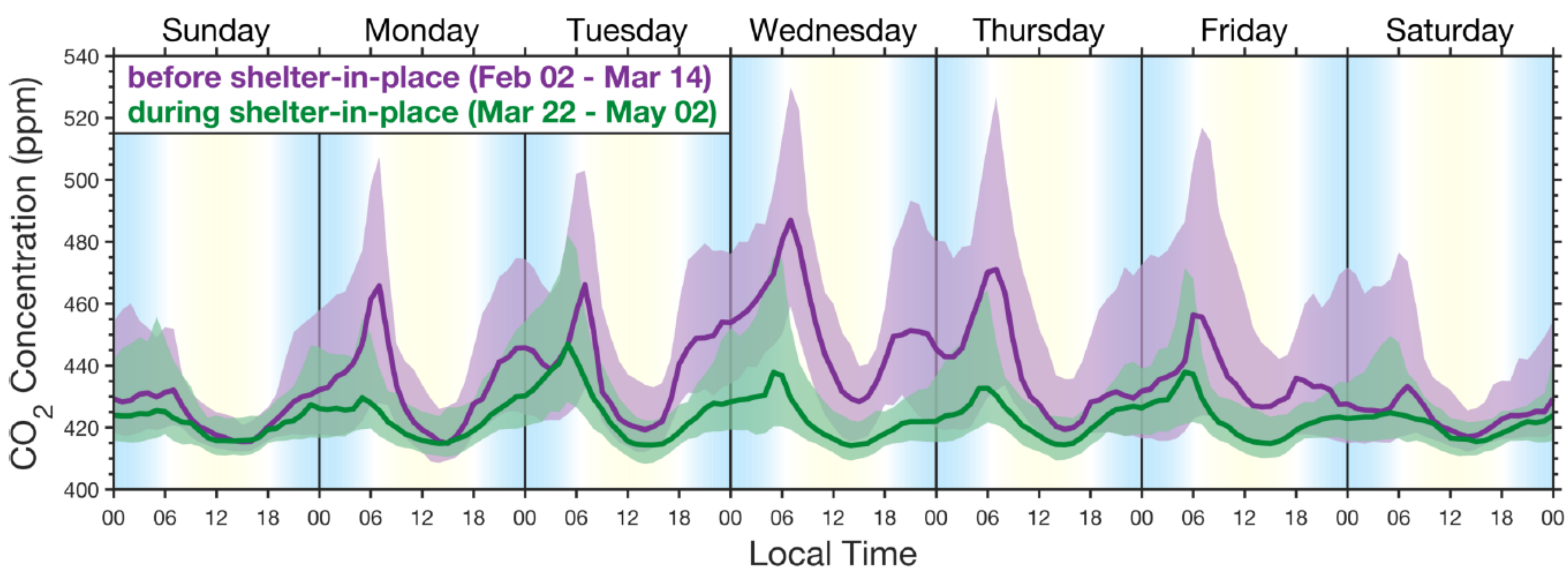
BEACO$_2$N CO_2 observations January – July 2020



http://beacon.berkeley.edu

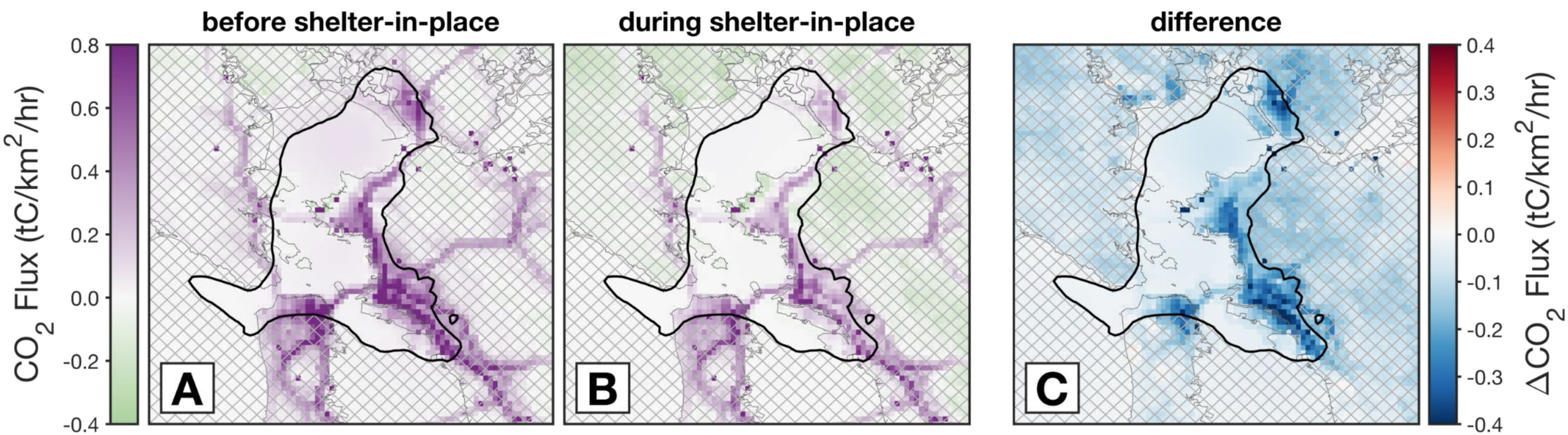

CARS
10^5
VMT
0
1
2
3
4
5
6
7
8
2020-02-01
2020-03-01
2020-04-01
2020-05-01
2020-06-01
2020-07-01


TRUCKS
10^4
VMT
0
1
2
3
4
5
6
7
2020-02-01
2020-03-01
2020-04-01
2020-05-01
2020-06-01
2020-07-01

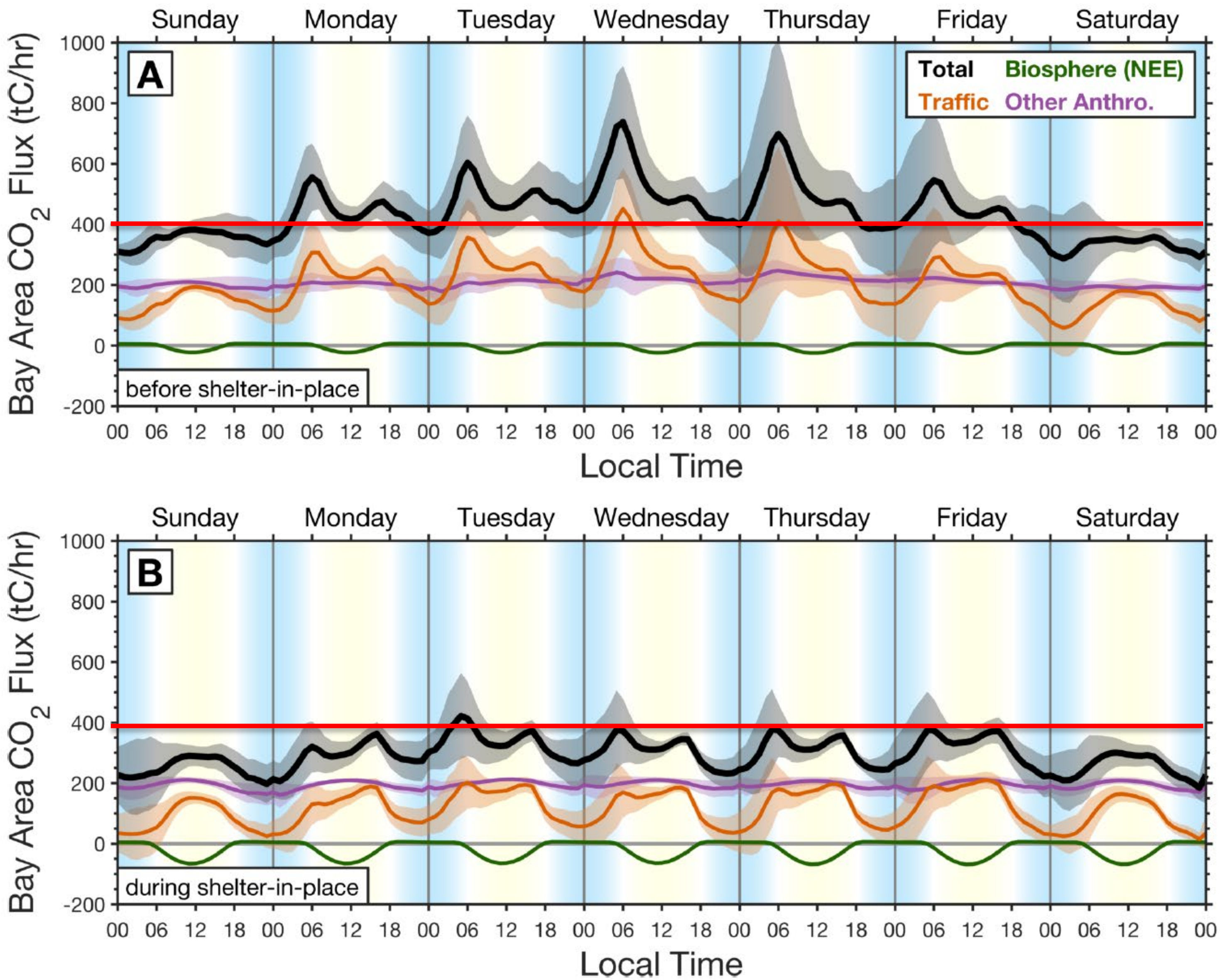


Sunday
Monday
Tuesday
Wednesday
Thursday
Friday
Saturday
before shelter-in-place (Feb 02 - Mar 14)
during shelter-in-place (Mar 22 - May 02)
CO2 Concentration (ppm)
540
520
500
480
460
440
420
400
00
06
12
18
Local Time

Results on a Map



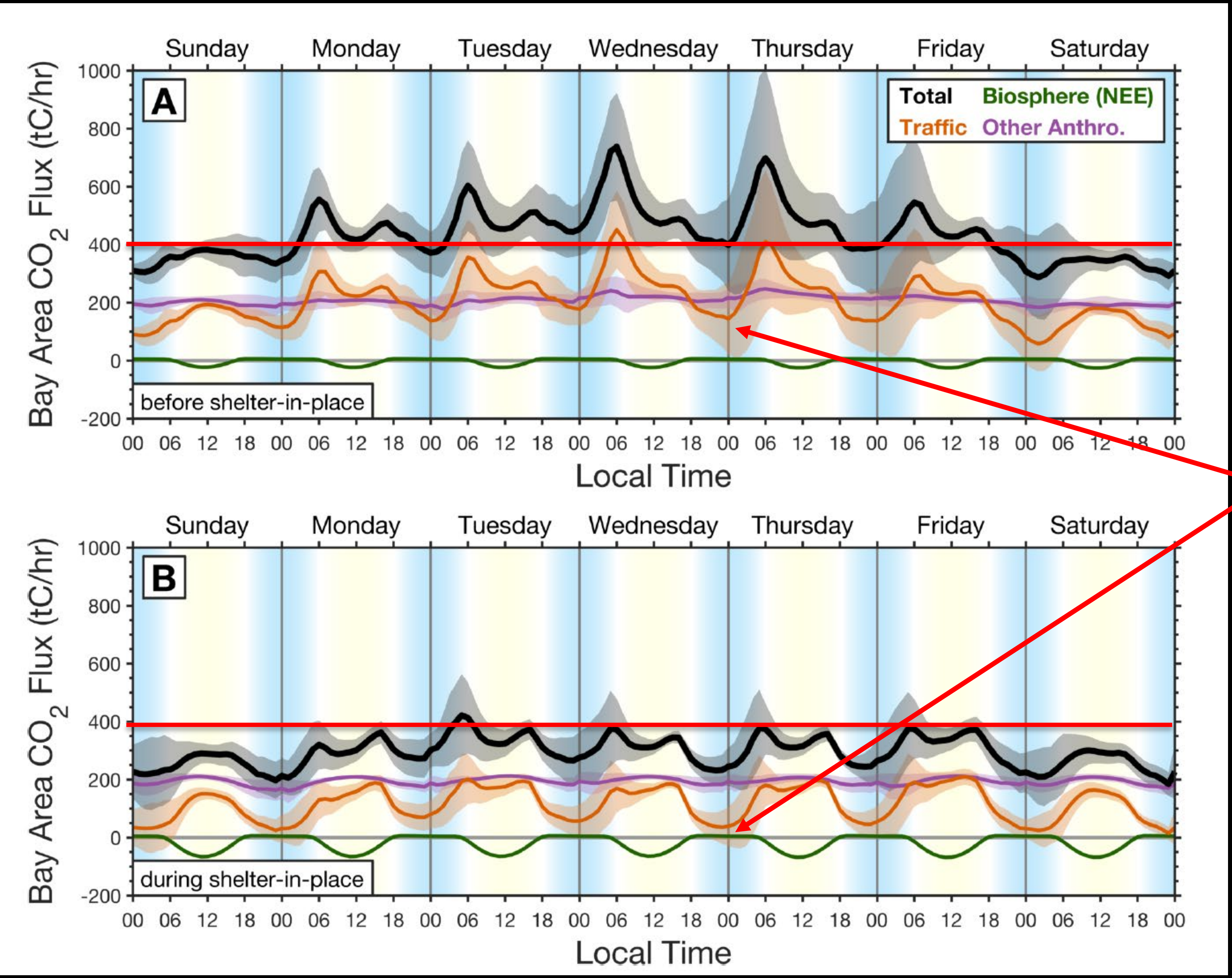
- **The emissions are best constrained inside the black line**
- **Largest changes on highways; emissions on city streets also changed**



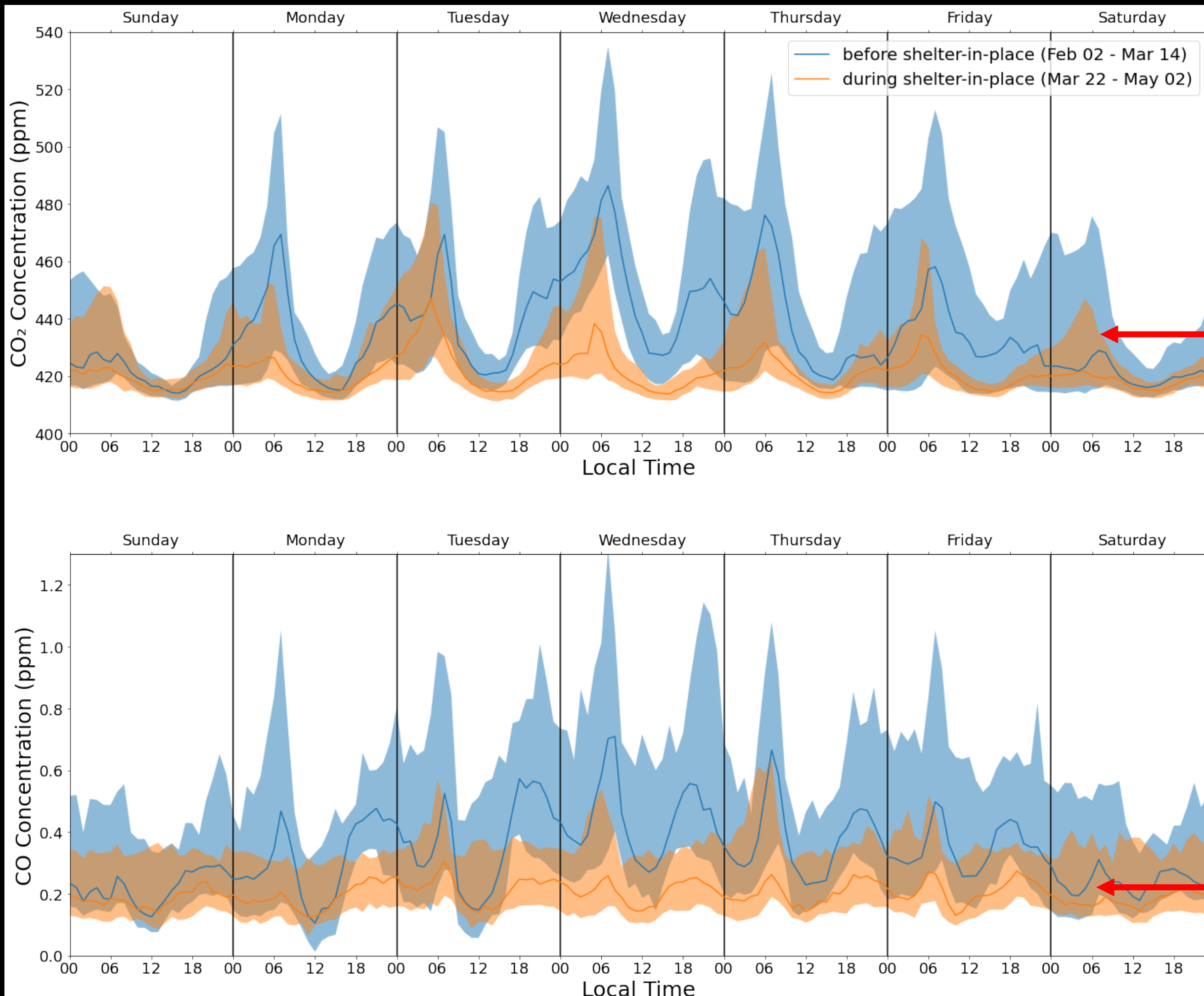
2020

Fluxes before and after COVID Shelter-in-place

25% reduction; 45% vehicle reduction



- **Nighttime emissions almost completely gone**

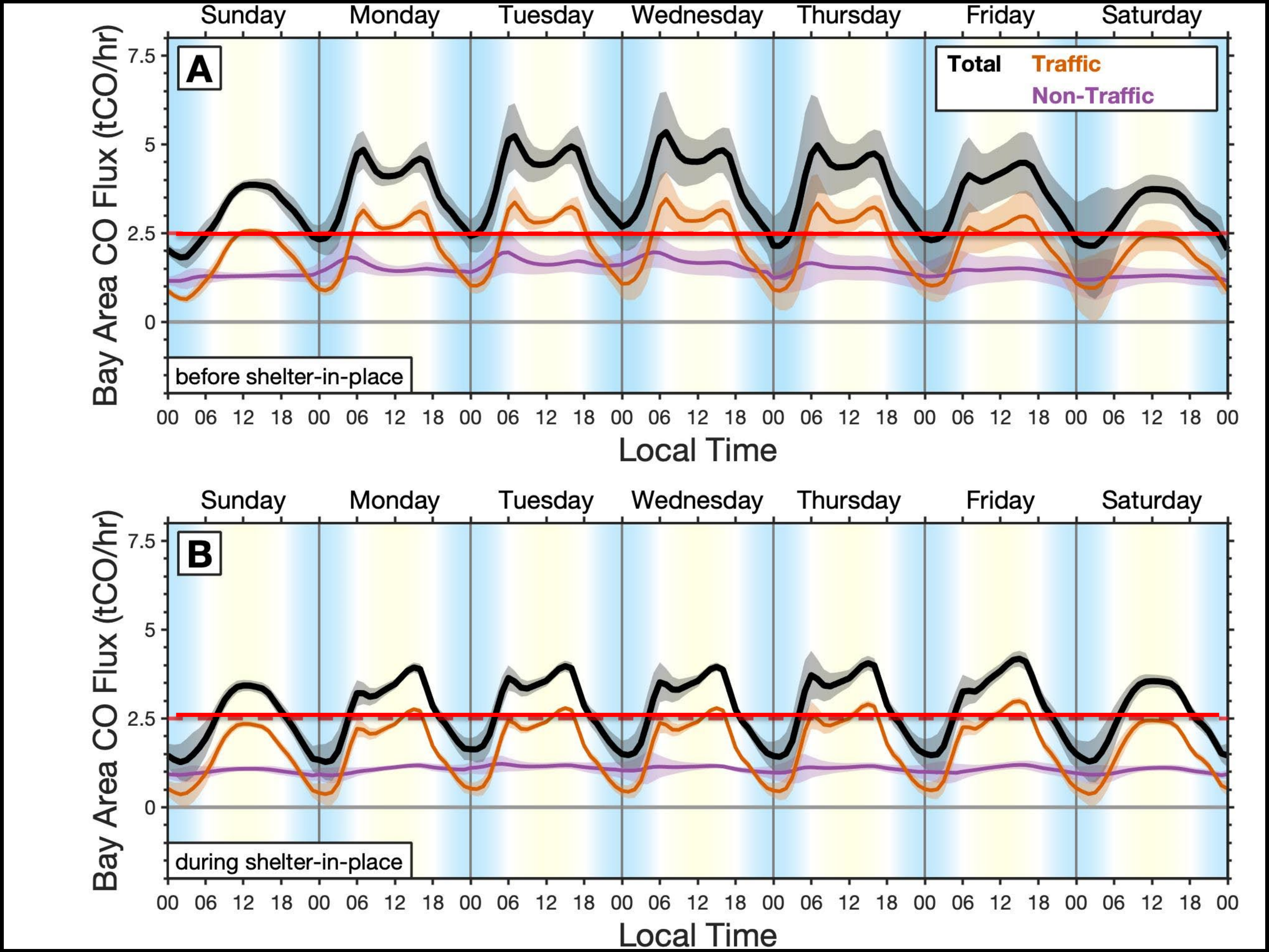


Naomi Asimow

- CO_2
- CO

BEACON

Carbon Monoxide Emissions from invesrion



What can we learn from dense mapping of air?

a) Emissions by sector in aggregate

b) Map of emissions for understanding
environmental justice and equity

c)emissions vs.
speed
catalytic convertors cold/hot
mix of cars and trucks

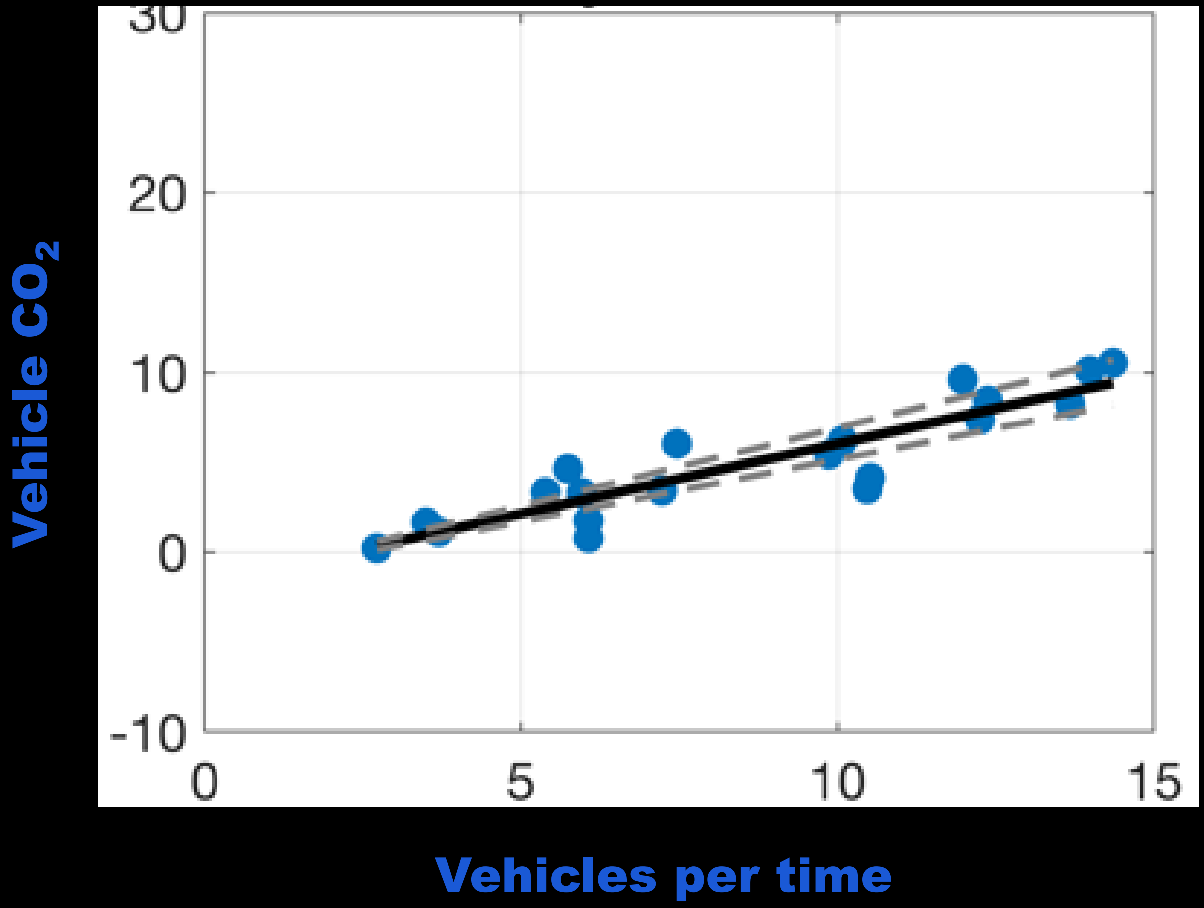
Process within each sector

How many cars/trucks at each moment in time?

How fast are they traveling?

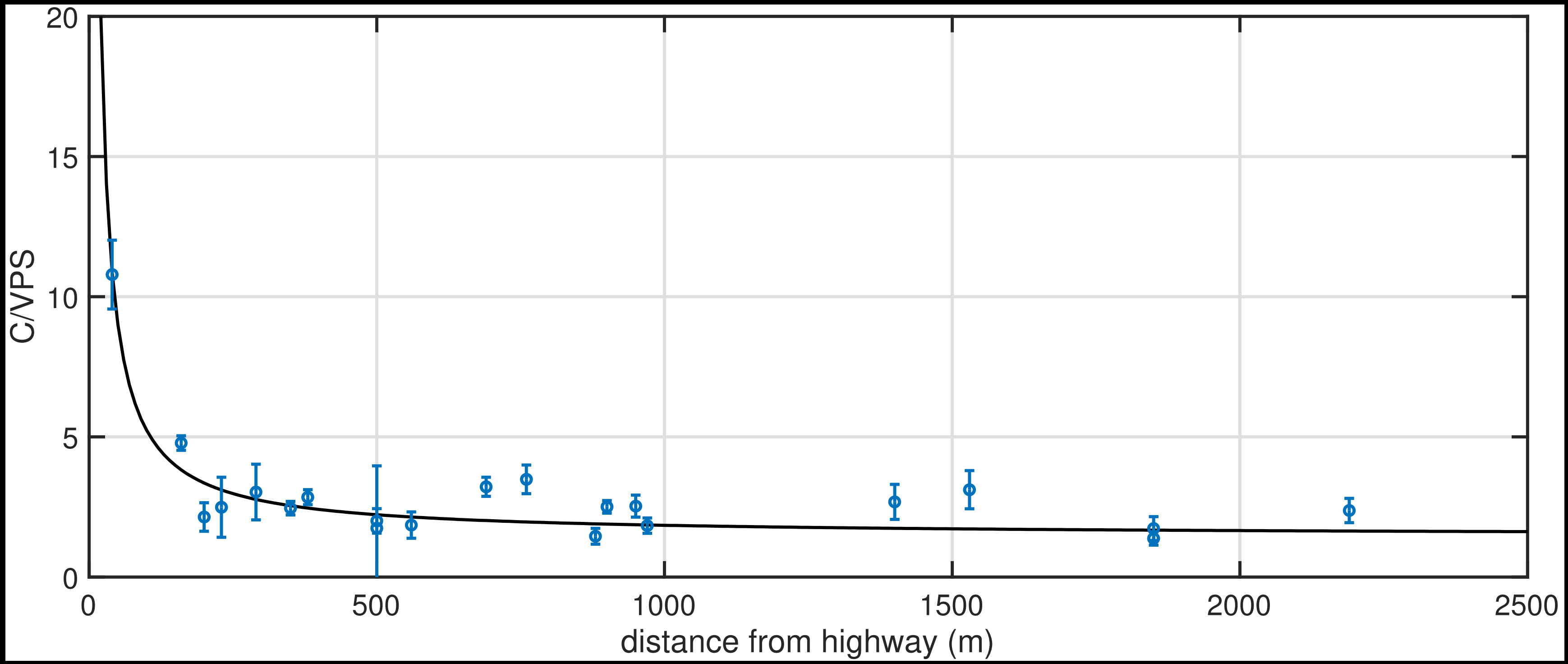
CO_2 (?) and other emissions at the speed of traffic?

Trends in annual emissions per vehicle

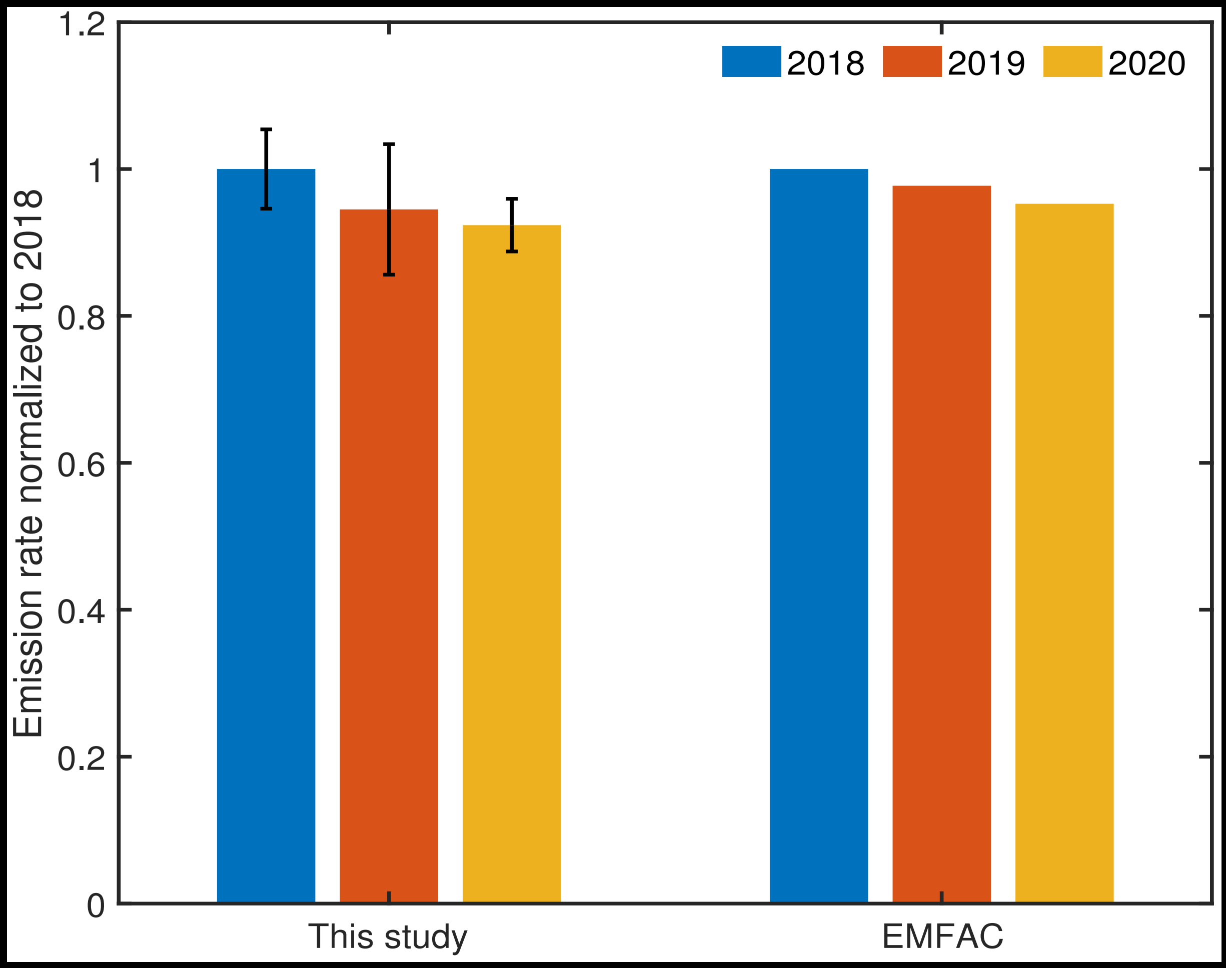


Kim et al. ES&T 2022

Emissions per vehicle vs distance from highway



Annual average emissions per vehicle obs and model

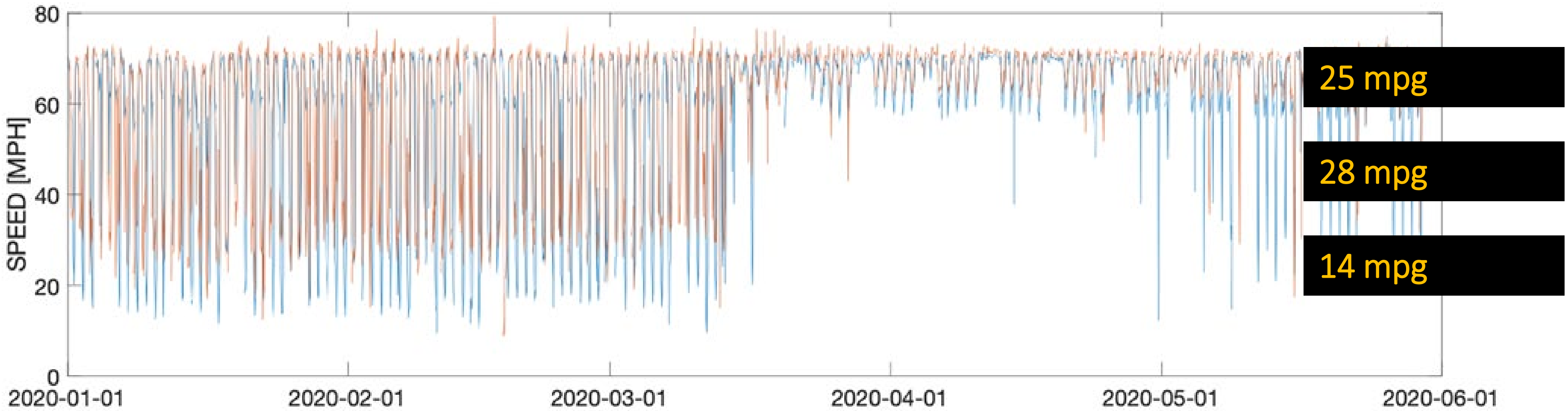


Kim et al. ES&T 2022

Emissions vs speed and HD Trucks

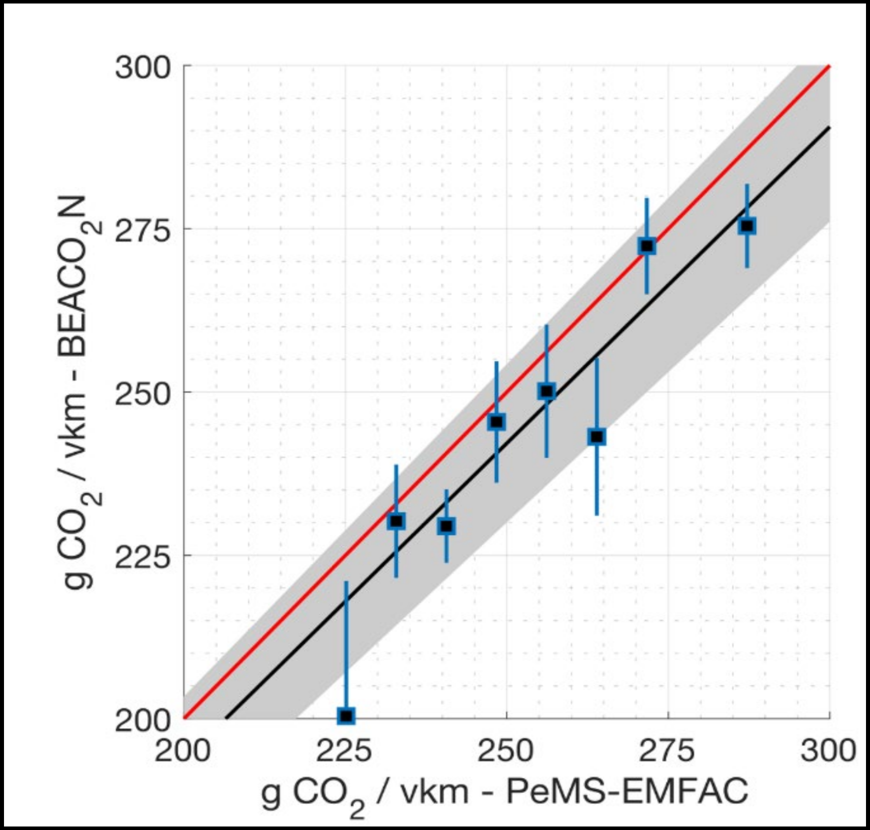
Helen Fitzmaurice

COVID Shutdown was not just the number of cars on the road, the early phase also eliminated congestion affecting fuel efficiency and EF for AQ gases and aerosol



Current fleet fuel efficiency vs. speed

From observations



Predictions

Slow speeds, less efficient

Optimal speeds, more efficient

BEACO$_2$N suggests entire vehicle fleet slightly more fuel efficient than predicted at all speeds. Confirms predicted speed dependence is accurate.

Fitzmaurice et al. ACP 2022

New locations with BEACO2N hardware

LA—Will Berelson—12 nodes

Glasgow, UK—25 nodes

Leicester, UK—Hartmut Boesch—10 nodes

Providence, RI—Meredith Hastings—25 nodes

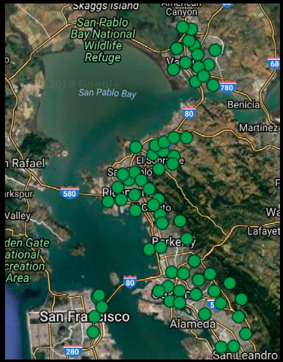
Data is live in near real time
http://beacon.berkeley.edu/about/

Conclusions and Outlook

High space and time resolution observations using networks with multiple chemicals and aerosol offer a new window into mechanisms affecting air in cities.

We are:

- **learning to interpret dense networks as more than the sum of individual instruments.**
- **learning to think about daily variability in ways that teach us about processes.**
- **constraining CO_2 emission trends from individual sectors with policy relevant precision and rapid timing**



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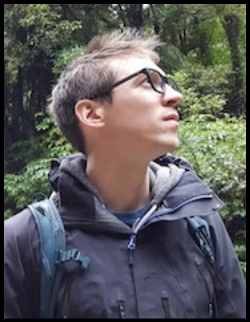

Alex Turner

Paul Wooldridge

Helen Fitzmaurice

Pietro Vannucci

Naomi Asimow

Yishu Zhu

Thank you!