Evaluating public-transit platforms as a cost-effective component of urban monitoring & initial observations during the Covid-19 lockdown

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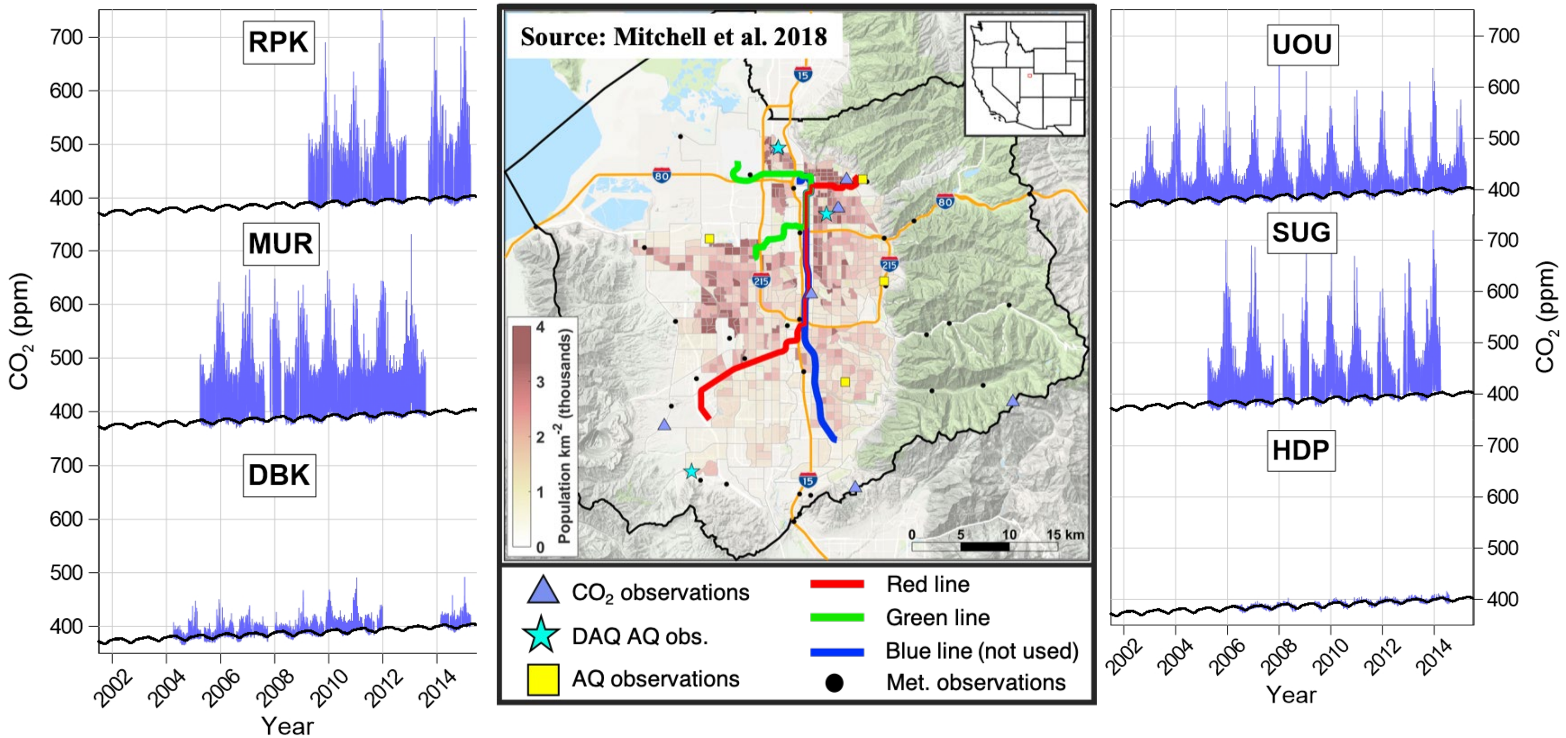
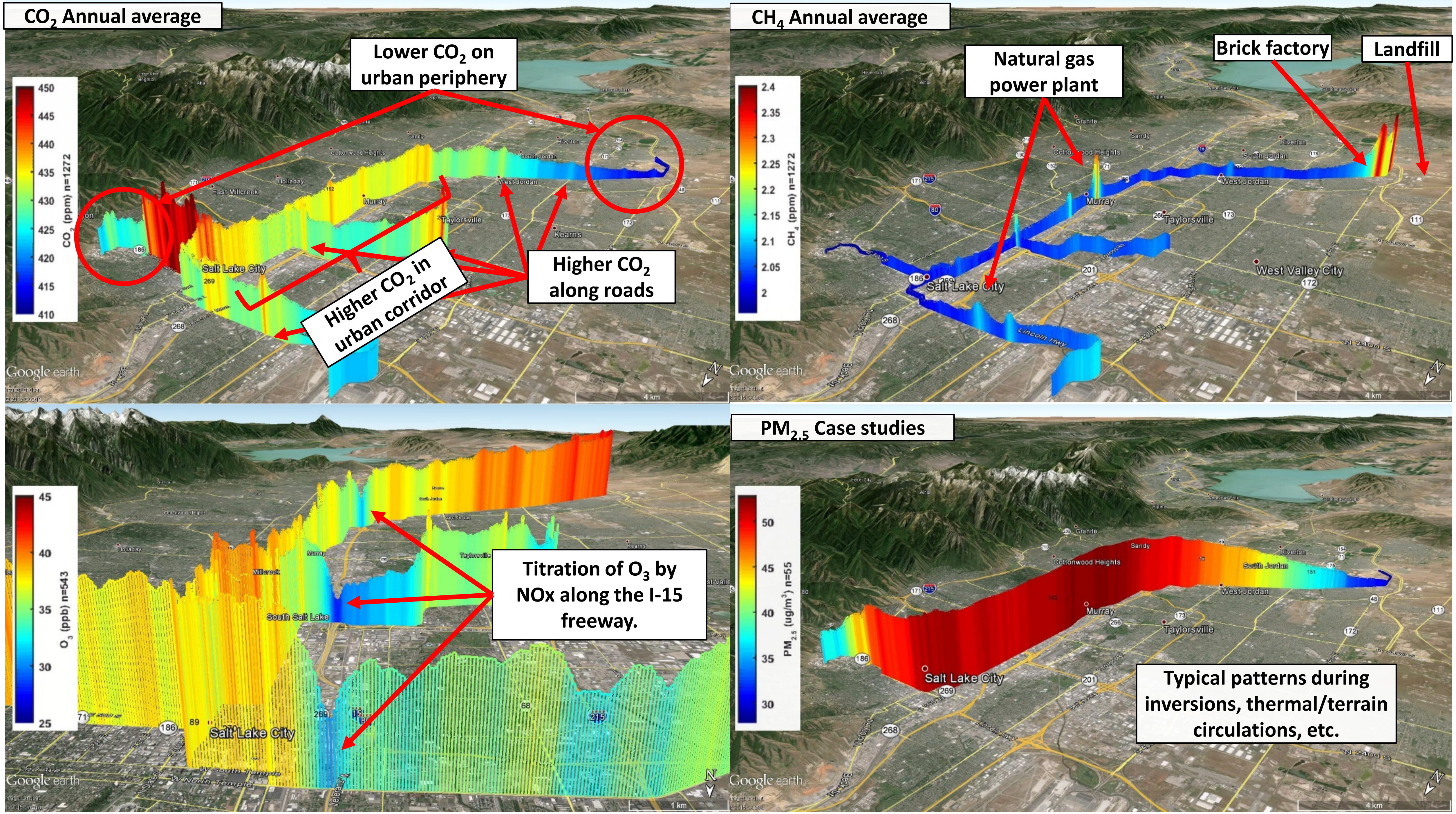
MINES AND EARTH SCIENCES | THE UNIVERSITY OF UTAH

Salt Lake City Monitoring:

- Developing novel monitoring strategies
- Addressing science & policy questions related to greenhouse gases and air pollutants

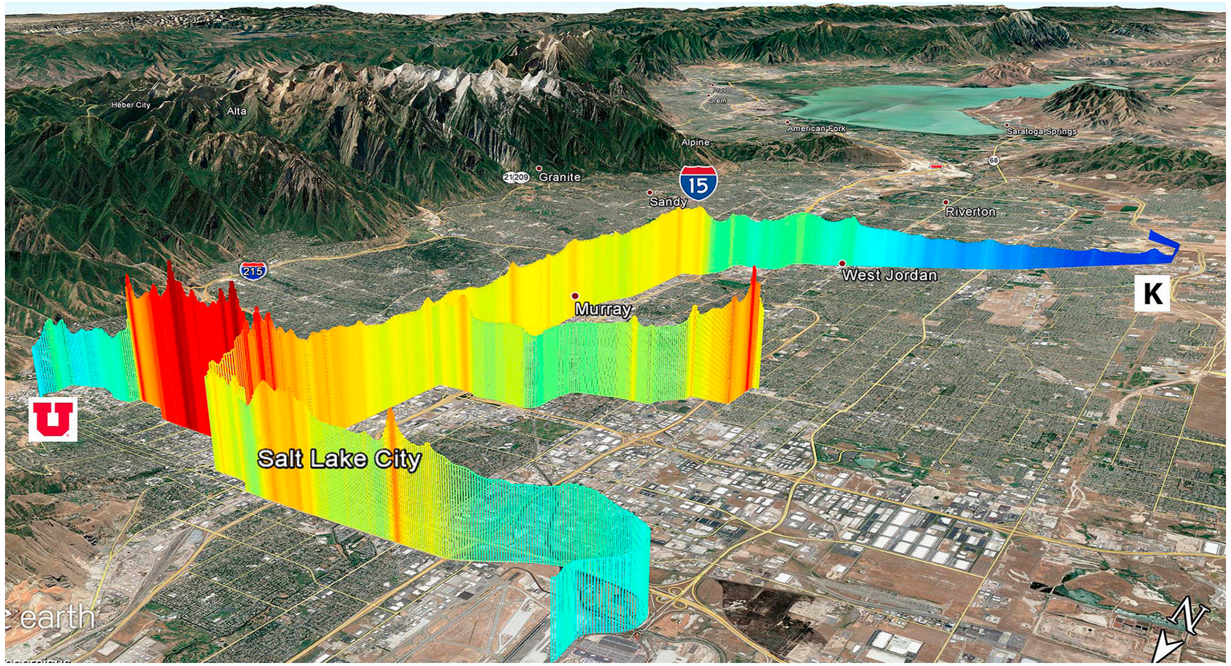
SLC network





CO_2 Annual average
Lower CO_2 on urban periphery
Higher CO_2 in urban corridor
Higher CO_2 along roads
CO_2 (ppm) n=1272
450
445
440
435
430
425
420
415
410
CH_4 Annual average
Natural gas power plant
Brick factory
Landfill
CH_4 (ppm) n=1272
2.4
2.35
2.3
2.25
2.2
2.15
2.1
2.05
2
O_3 (ppb) n=543
45
40
35
30
25
Titration of O_3 by NOx along the I-15 freeway.
$PM_{2.5}$ Case studies
$PM_{2.5}$ (ug/m^3) n=55
50
45
40
35
30
Typical patterns during inversions, thermal/terrain circulations, etc.
Salt Lake City
Google earth

Scientific question: *What is the value of near-surface mobile CO_2 observations?*



- Does incorporating mobile CO_2 observations offer meaningful improvements relative to traditional observation networks?

- How can this be quantified? What are the implications for urban monitoring network design?

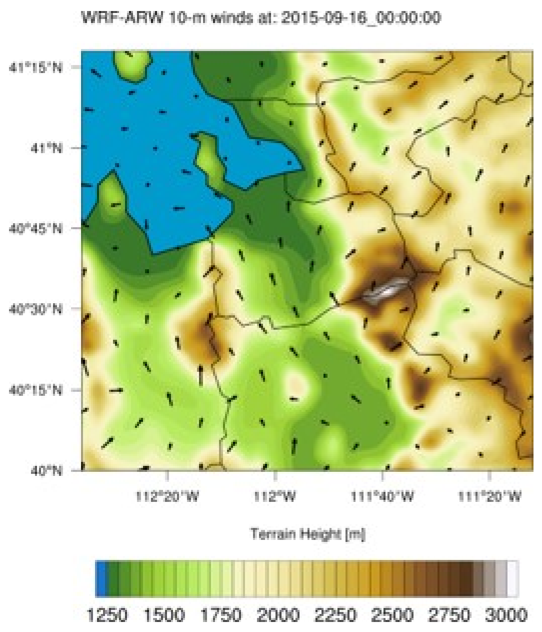
- We use an **inverse modeling framework** where mobile and non-mobile measurements are used to constrain urban CO_2 emissions

Inverse modeling framework

z: Observations

$$\hat{\mathbf{s}} = \mathbf{s}_p + (\mathbf{HQ})^T(\mathbf{HQH}^T + \mathbf{R})^{-1}(\mathbf{z} - \mathbf{Hs}_p)$$

Spatiotemporal influence ‘H’

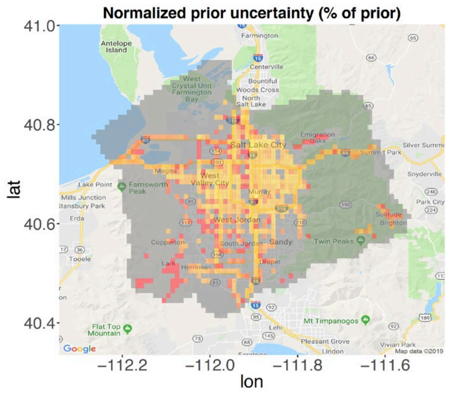


STILT backward trajectories driven by WRF, with WRF runs optimized based in results in Mallia et al. (2015)

Prior covariance matrix ‘Q’

$$\mathbf{Q} = \mathbf{I}_\sigma(\mathbf{D} \otimes \mathbf{E})\mathbf{I}_\sigma$$

$\mathbf{I}_\sigma$ = diagonal matrix that describes prior uncertainties



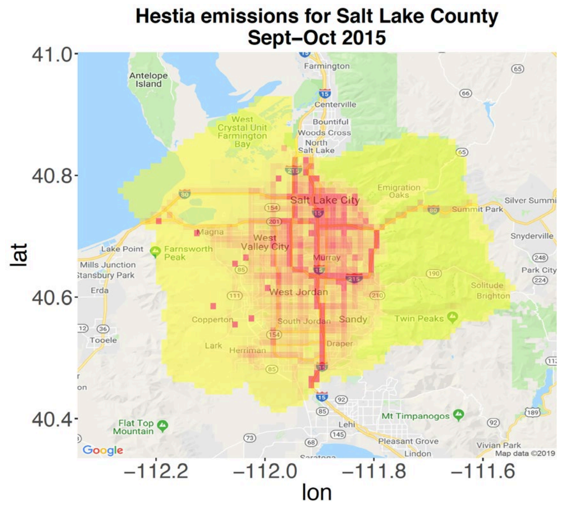
$\mathbf{E}$ = spatial covariance matrix

$$\mathbf{E} = \left[\exp\left(-\frac{\mathbf{X}_s}{l_s}\right)\right]$$

$\mathbf{D}$ = temporal covariance matrix

$$\mathbf{D} = \left[\exp\left(-\frac{\mathbf{X}_\tau}{l_\tau}\right)\right]$$

Prior ‘S_p’



‘R’ matrix

R_{part} = .1 ppm

R_{aggr} = 40% of mean enhancement

R_{eddy} = 0 ppm

R_{bg} = 1.9 ppm

R_{PBL} = 7% of mean enhancement

R_{trans} = 35% of mean enhancement

R_{bio} = 25% of bio enhancement

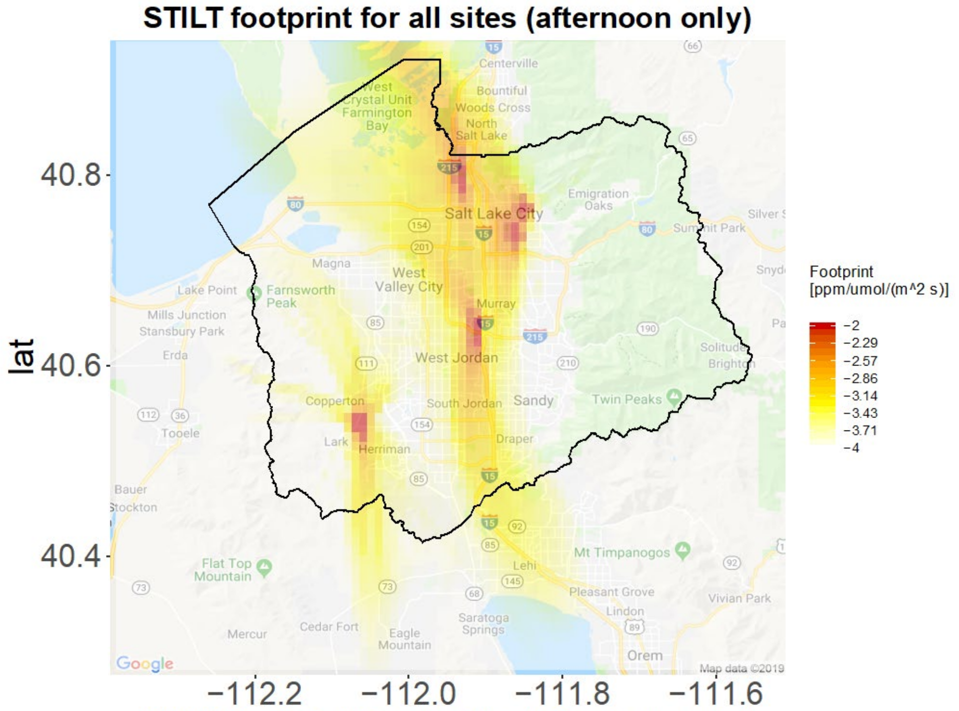
R_{instru} = .25 ppm

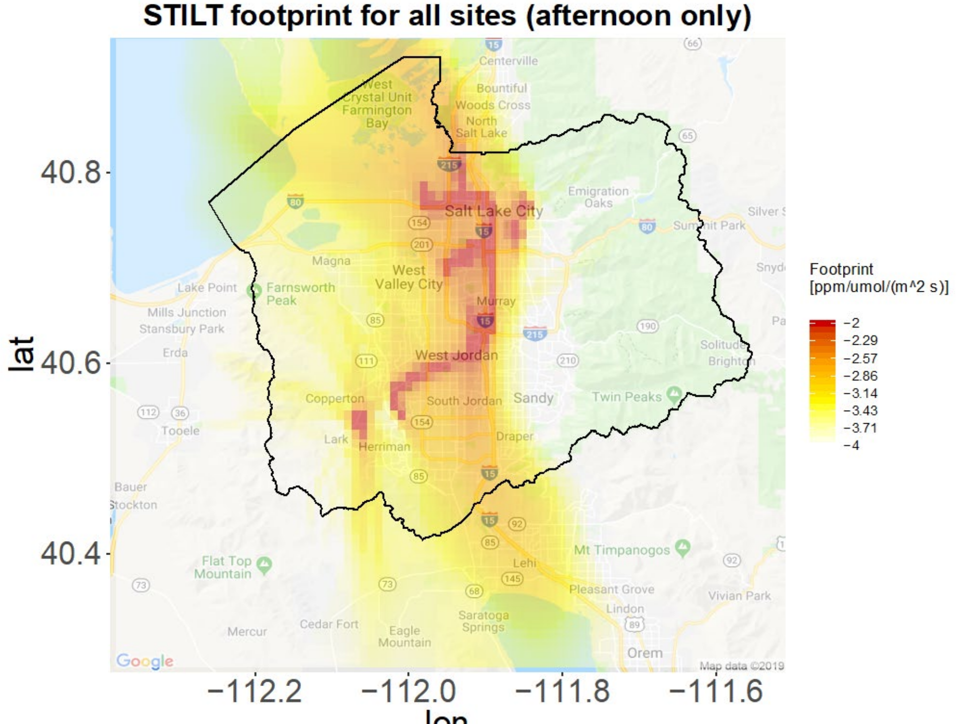
4 Inversions were carried out:

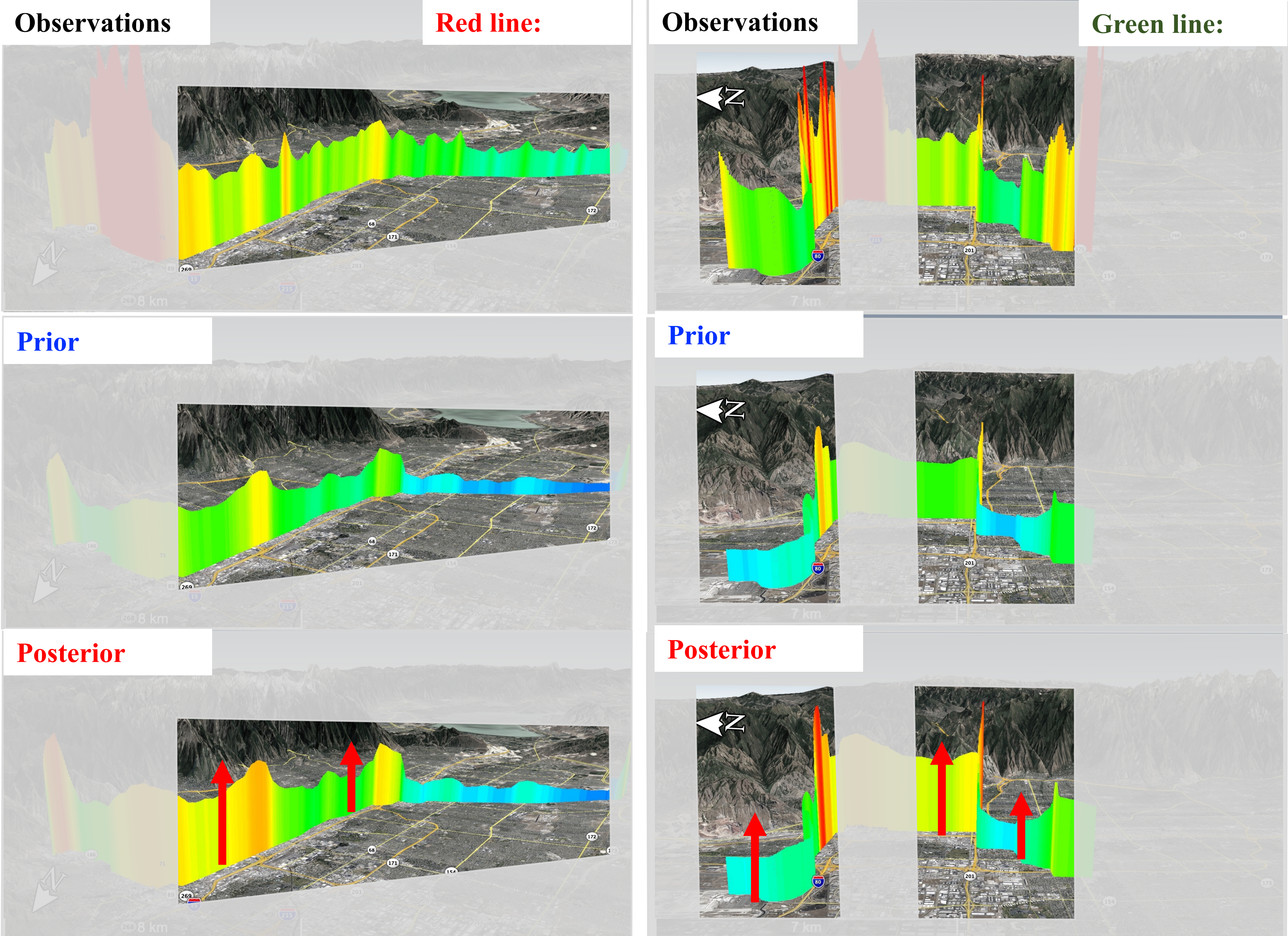
1. Inversion with stationary sites only (DBK, WBB, SUG, and RPK)
2. Configuration with stationary and mobile observations (TRAX Red and Green Lines)
3. TRAX data only (red & green line)
4. SUG site only (our most centrally located station)

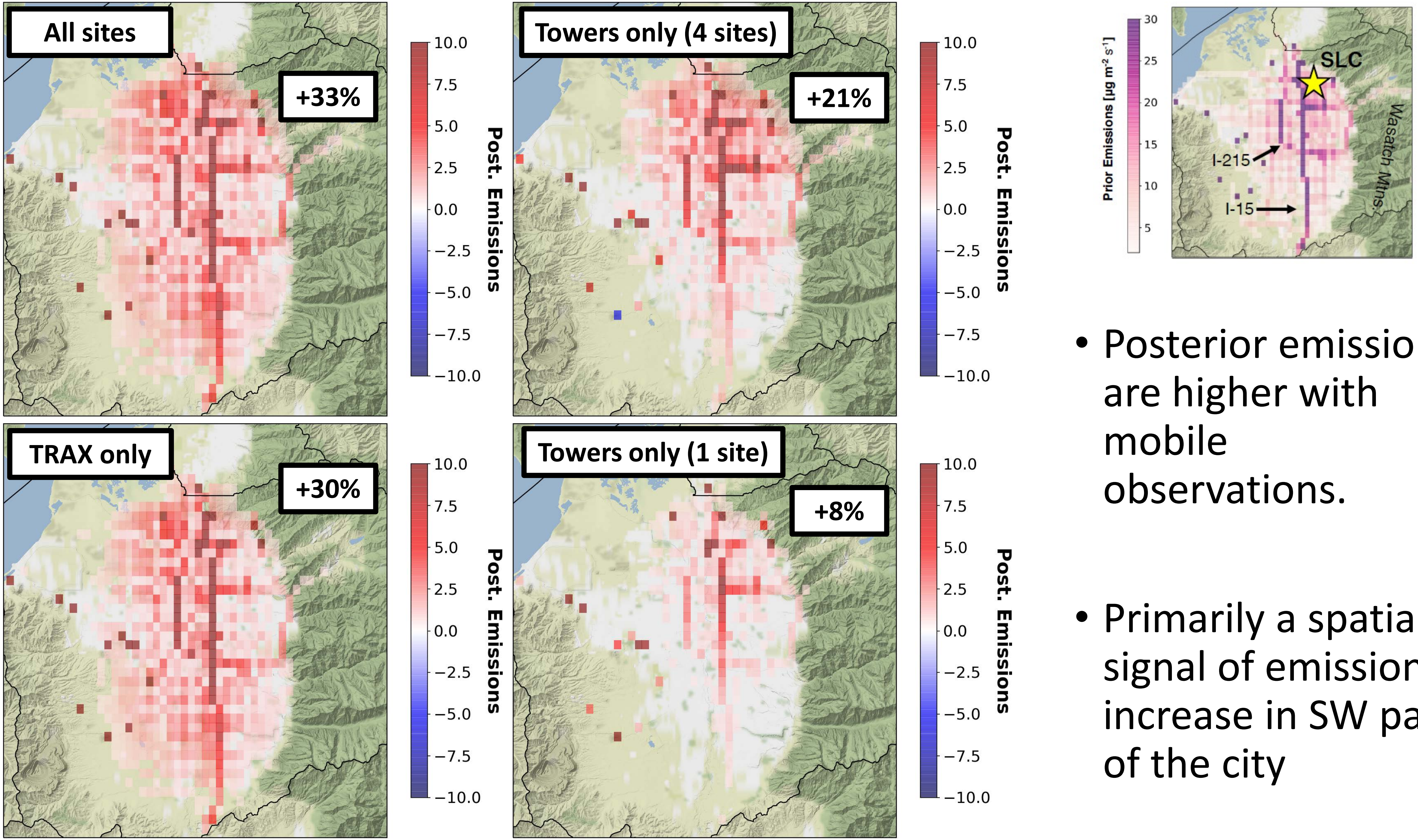
TRAX data points along roadways excluded to avoid issues with tail pipe emissions

Inversions only performed during the afternoon (1800-2300 UTC)

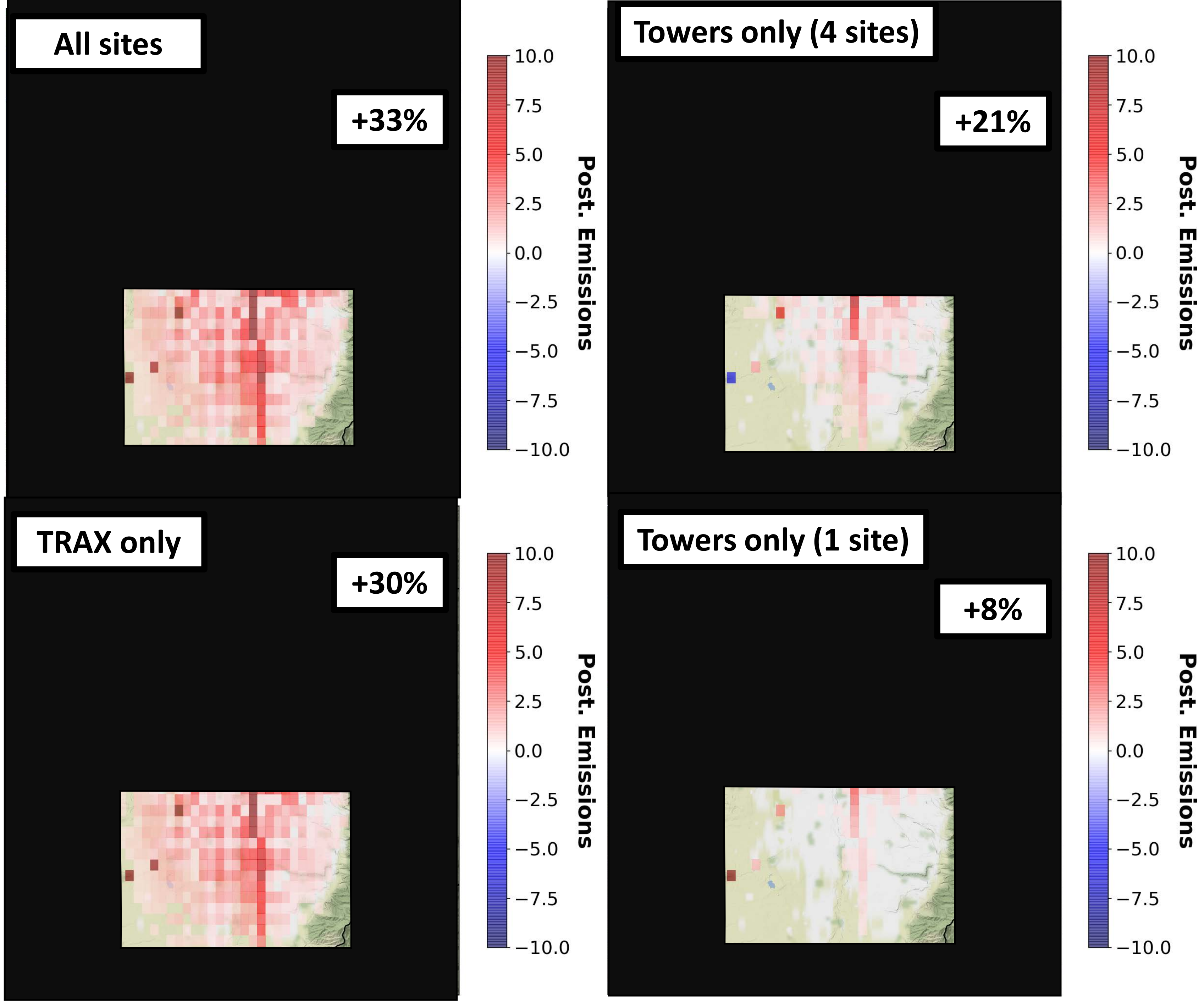


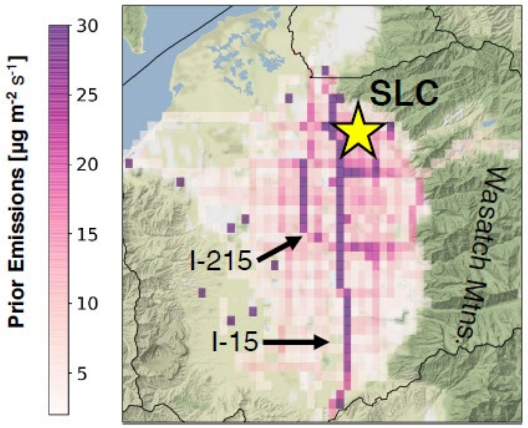



Observations
Red line:
Observations
Green line:
Prior
Prior
Posterior
Posterior
8 km
7 km



- Posterior emissions are higher with mobile observations.
- Primarily a spatial signal of emissions increase in SW part of the city





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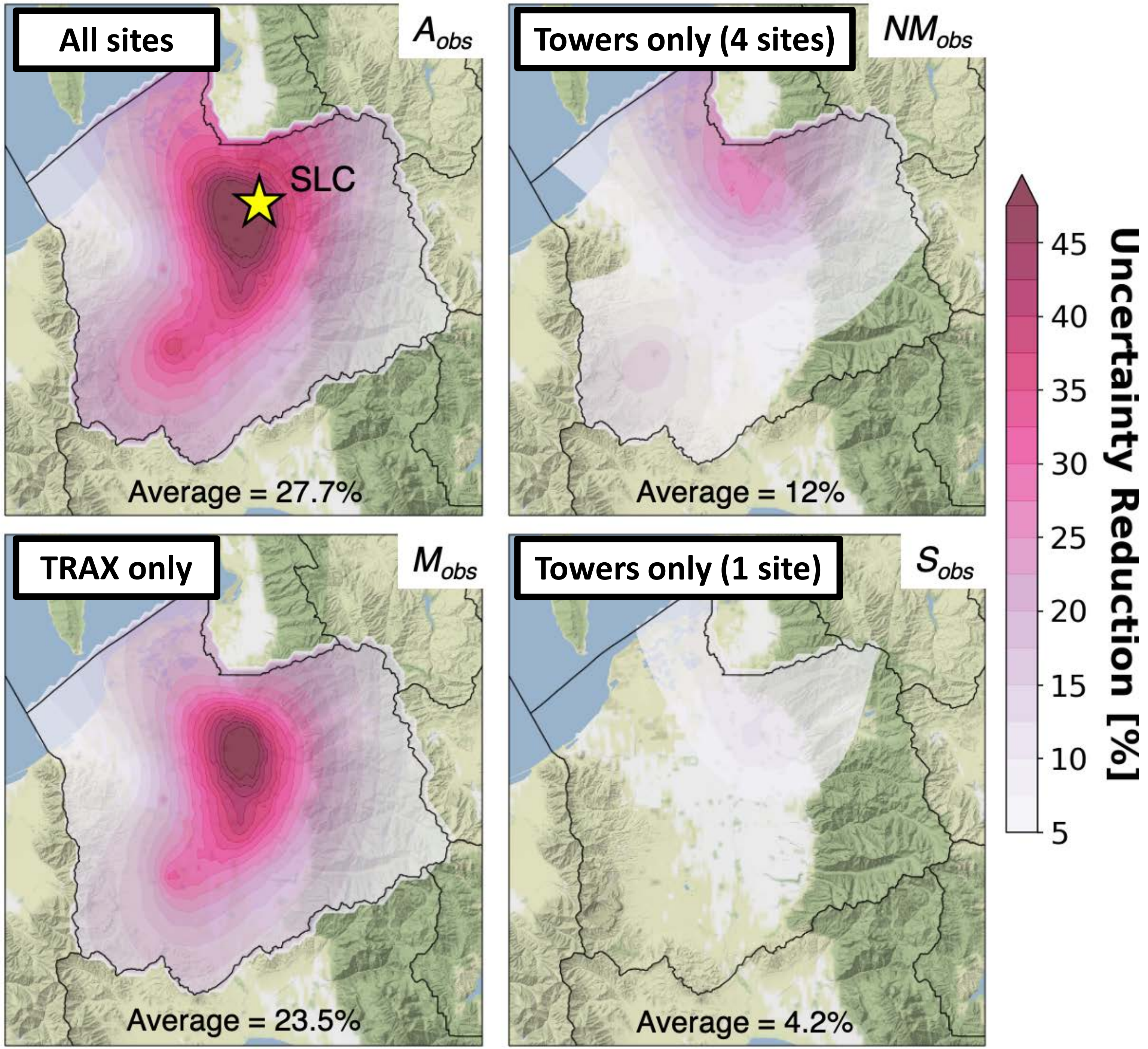


- Uncertainty covariance matrix quantifies the reduction in emission uncertainty.

- Key point:

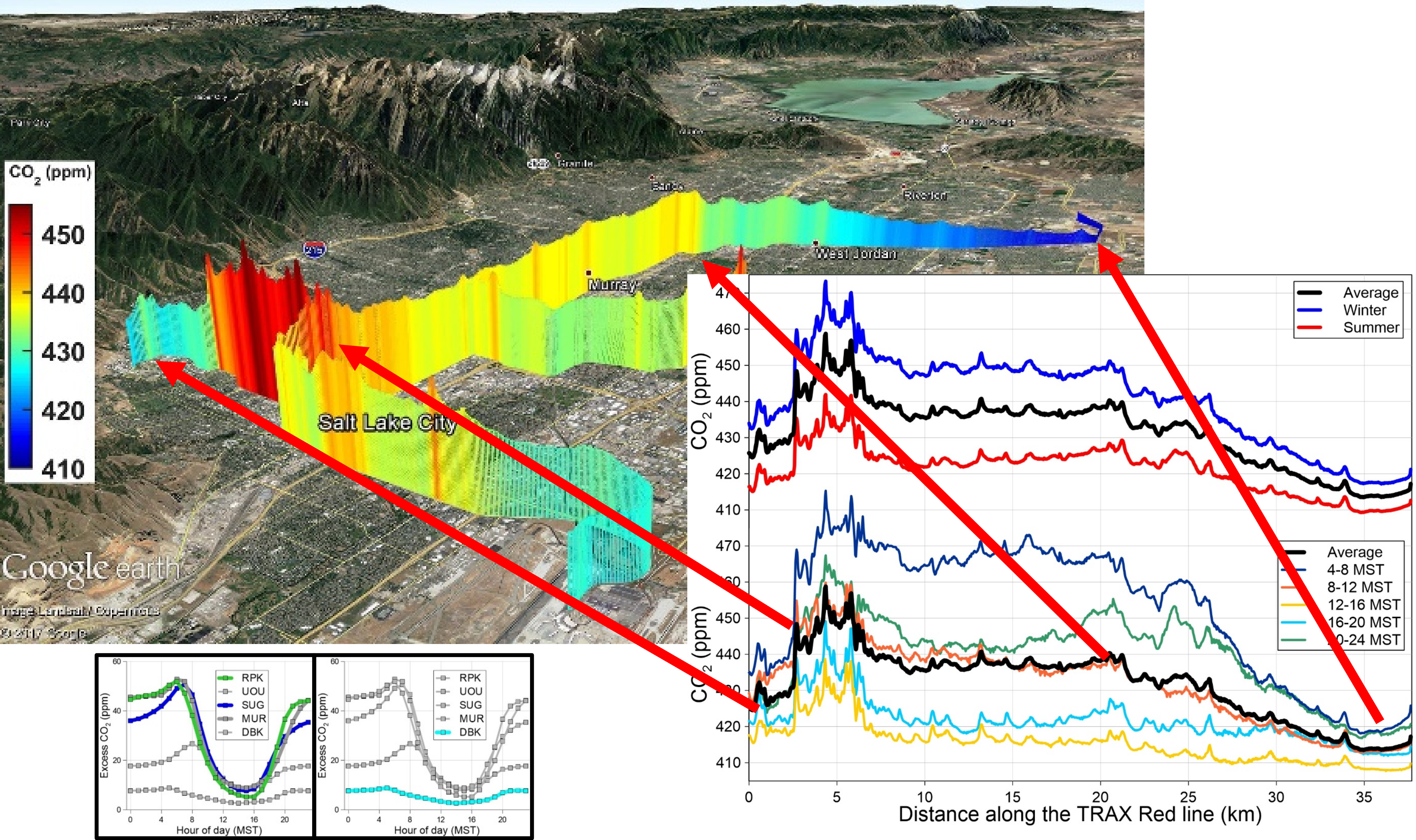
Uncertainty reduction with 1 mobile site is > 4 stationary sites

- Implications for urban monitoring network design

Emission signal magnitude is inversely proportional to the footprint

Monitor location	Footprint	Signal magnitude	Obs type
Point source	Small	Large	Flux tower
City scale	Medium	Medium	~100m tower or building
Regional	Large	Small	Aircraft or satellite

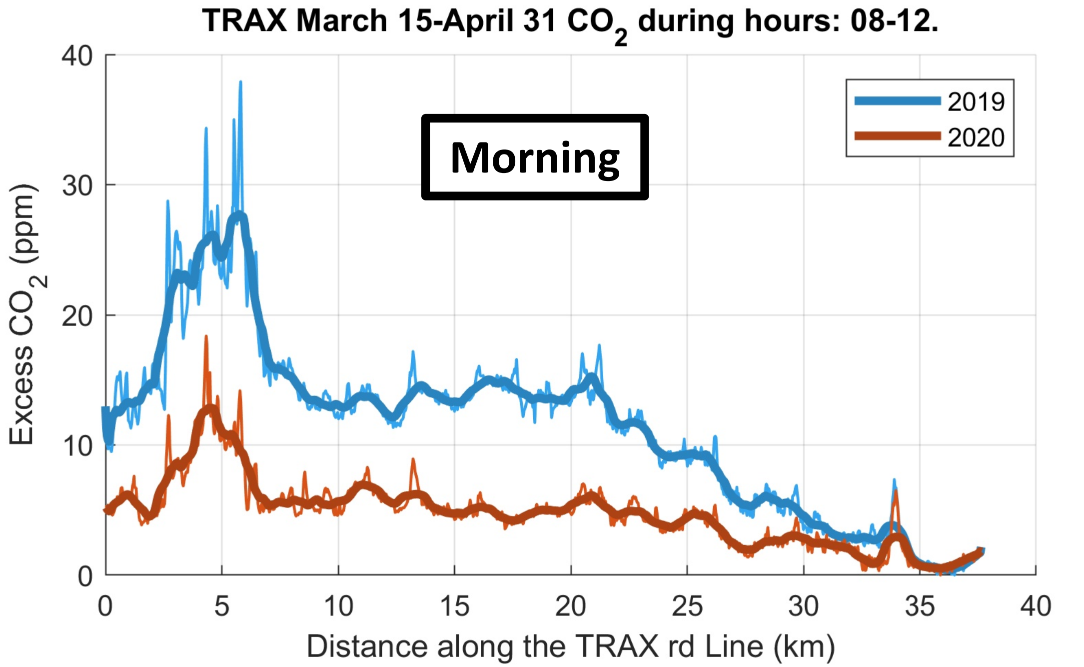
- Big question: What is the optimal urban observing system to detect changes in emissions?
- Public transit is a blend of near surface observations that also have a city spatial scale.
- The Covid-19 lockdowns are a “natural experiment” to test urban monitoring systems.

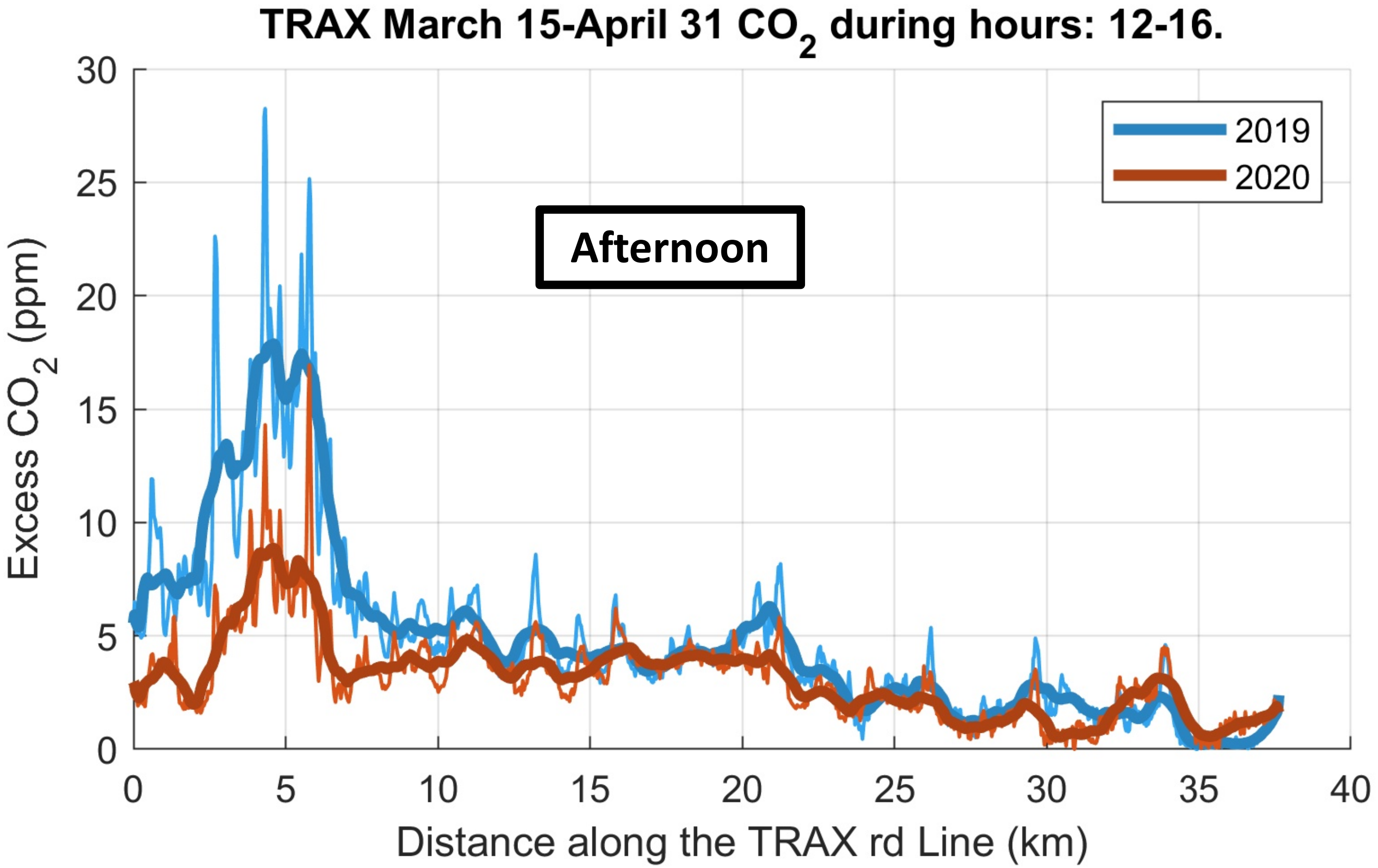


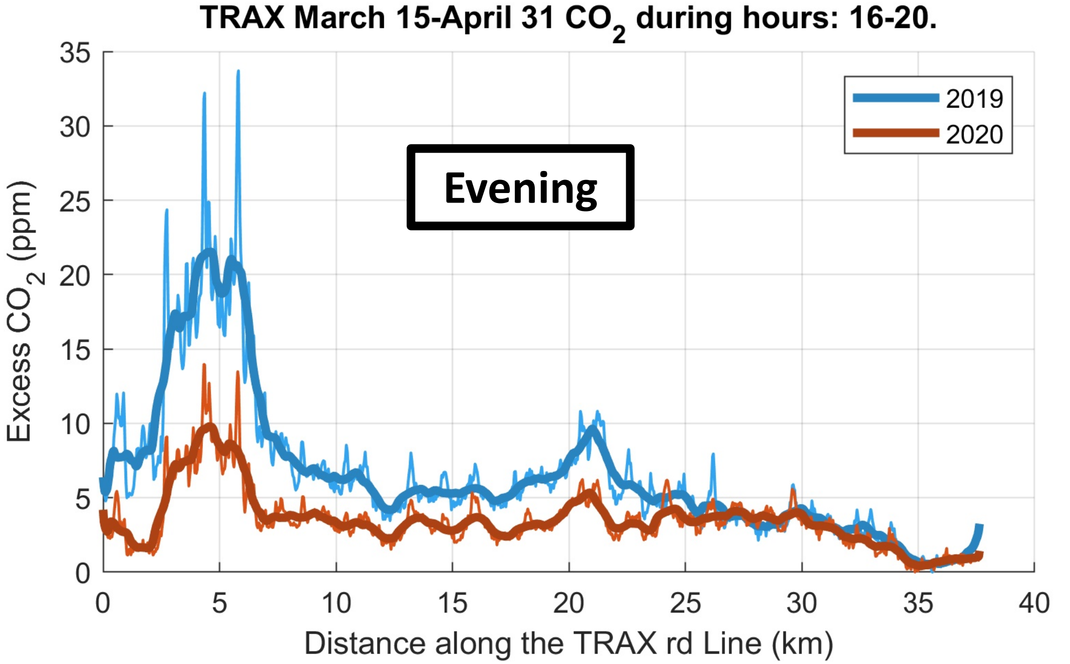
CO_2 (ppm)
450
440
430
420
410
Salt Lake City
Murray
West Jordan
Riverton
Google earth
Average
Winter
Summer
Average
4-8 MST
8-12 MST
12-16 MST
16-20 MST
CO_2 (ppm)
Distance along the TRAX Red line (km)
0
5
10
15
20
25
30
35
RPK
UOU
SUG
MUR
DBK
Excess CO_2 (ppm)
Hour of day (MST)

CO_2 during Covid-19 Lockdown:

- 2020 had lower excess CO_2
- Afternoon reduction prominent around downtown & major roads







Summary

- The mobile TRAX network has a positive impact on our inversion

- A single public transit-mounted instrument:
  - Significantly outperforms a single stationary site
  - Comparable to a high-precision CO_2 network with 4 stations (**~$50,000 vs. $200,000 dollars**)
  - Produces a large reduction of uncertainty over a broad urban area

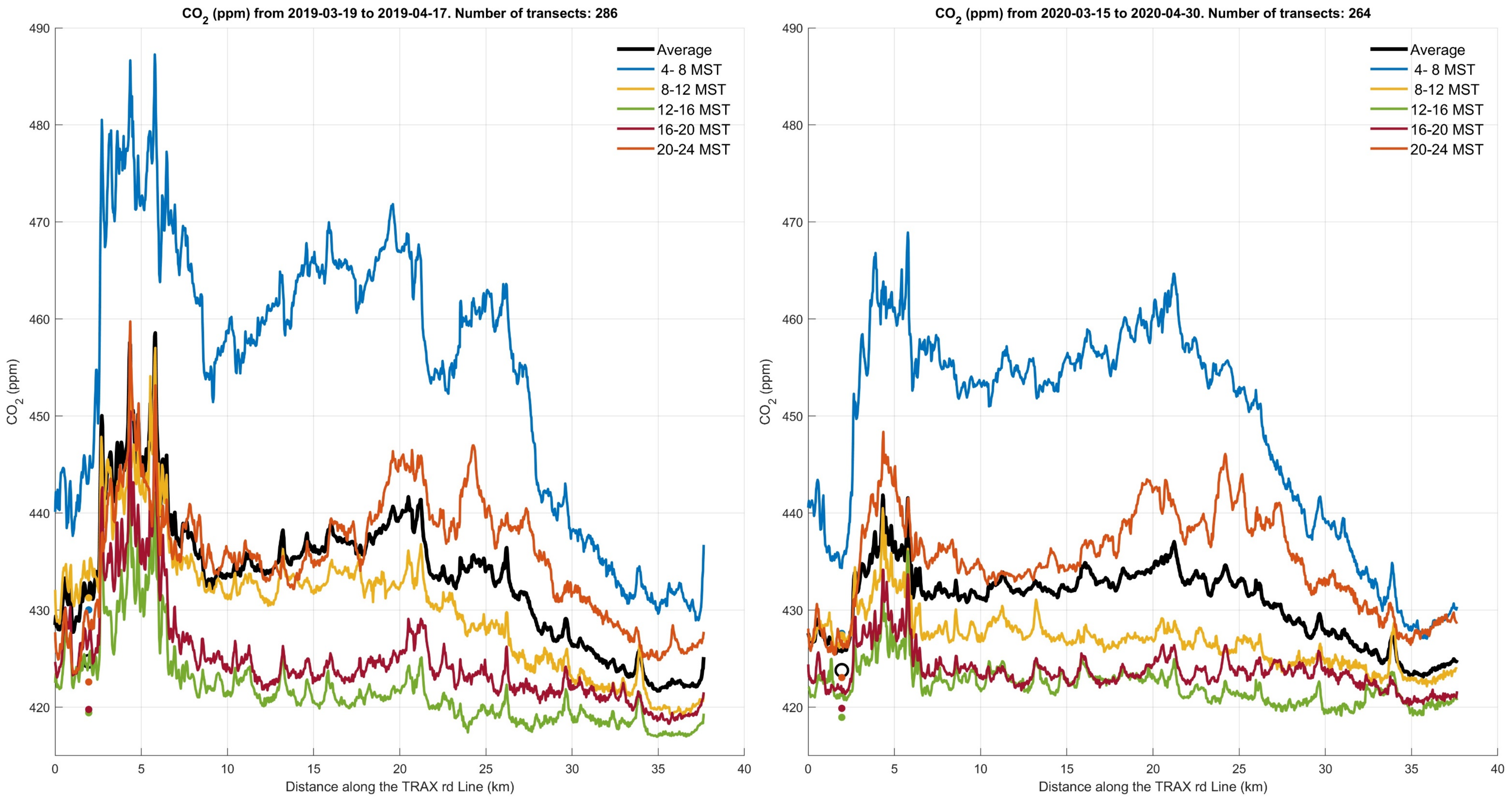
- Results are promising. Can it be reproduced in another city? Using electric buses?

- Covid-19 lockdown is a unique natural experiment to test monitoring capabilities. Observations show a large springtime 2019-2020 difference in excess CO_2. WRF simulations starting today…

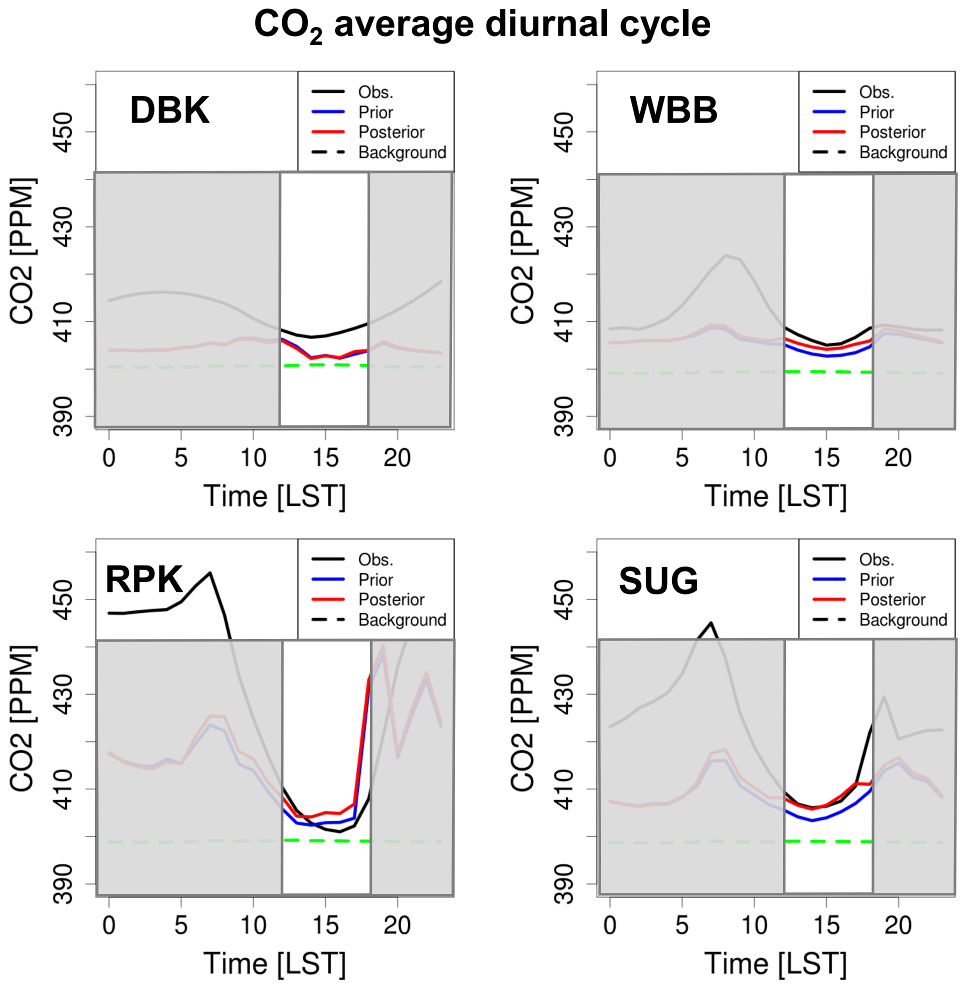
Thanks To:

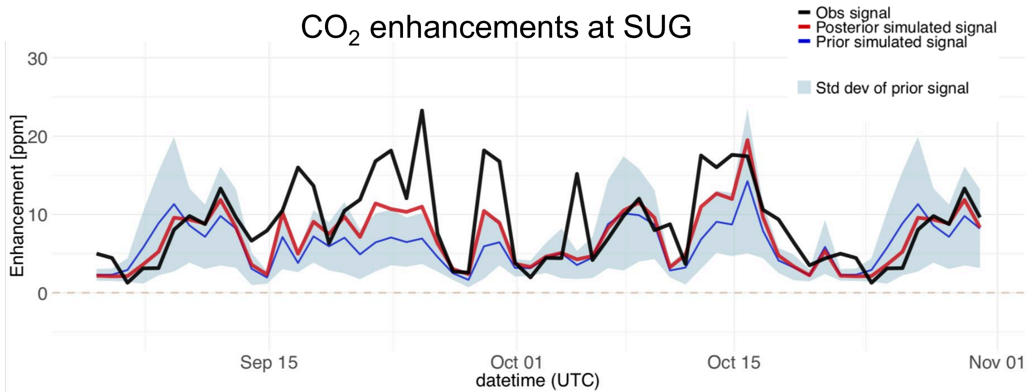

NATIONAL OCEANIC AND ATMOSPHERIC ADMINISTRATION
U.S. DEPARTMENT OF COMMERCE
NOAA
AC4
Atmospheric Chemistry,
Carbon Cycle, and Climate
UTA TRAX

Extra slides



CO2 (ppm) from 2019-03-19 to 2019-04-17. Number of transects: 286
Average
4- 8 MST
8-12 MST
12-16 MST
16-20 MST
20-24 MST
CO2 (ppm)
Distance along the TRAX rd Line (km)
CO2 (ppm) from 2020-03-15 to 2020-04-30. Number of transects: 264





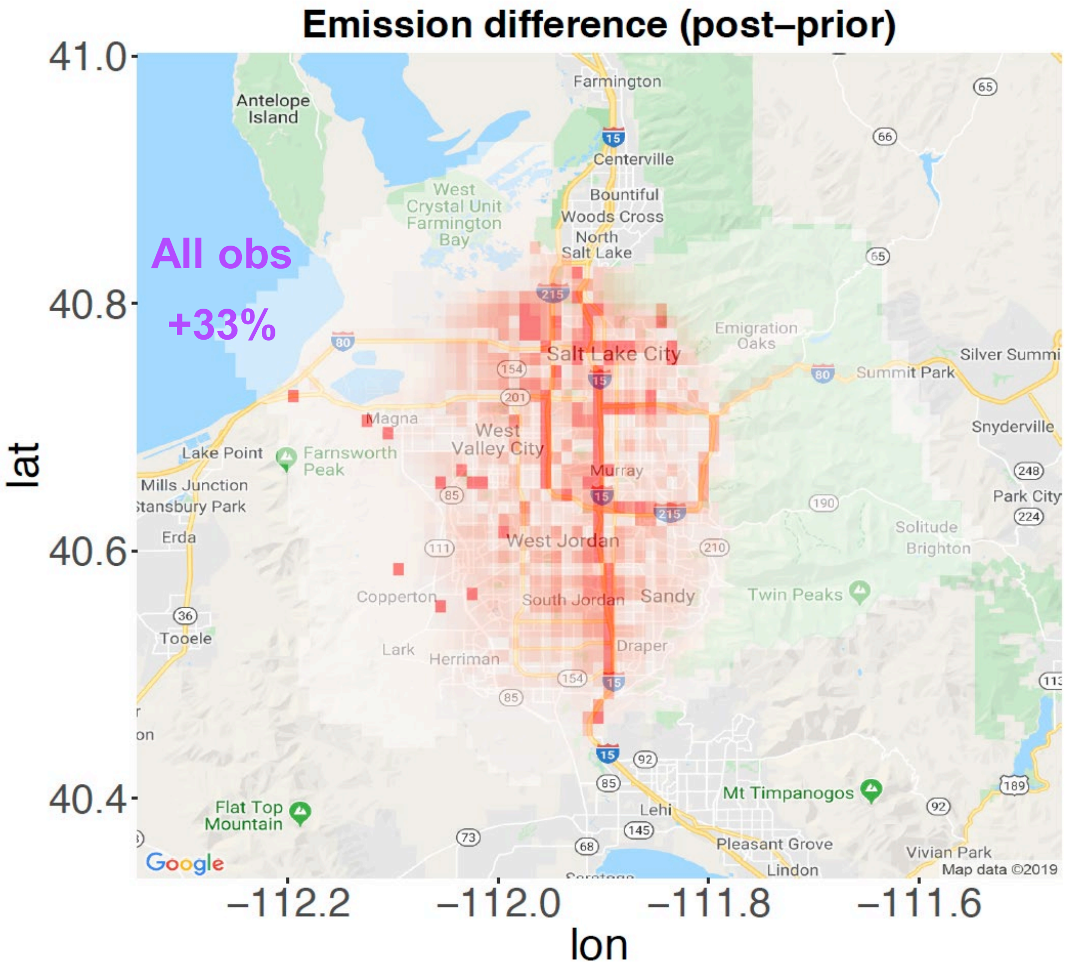
General results:

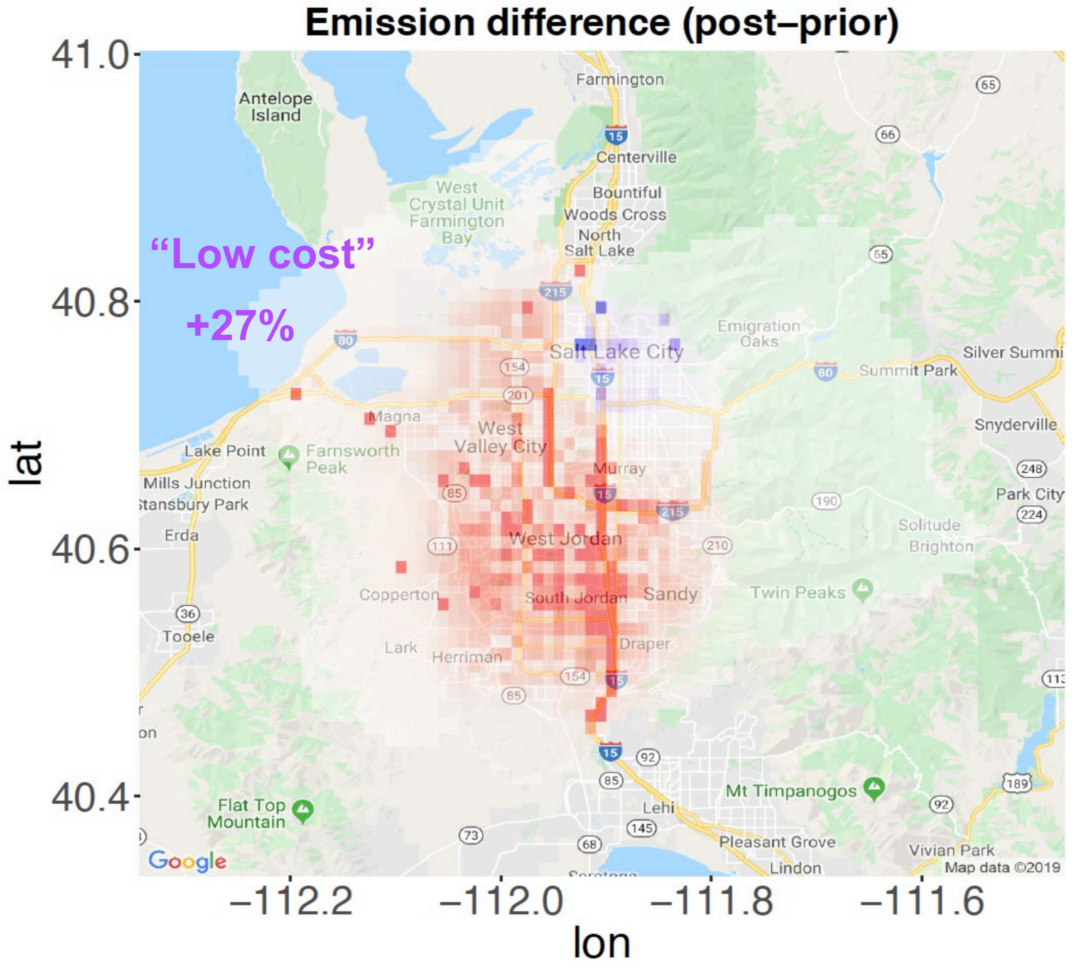
- Simulations using CO_2 observations from TRAX + stationary sites performed reasonably from Sept-Oct 2015

- Corrections only applied during mid-afternoon

- SUG was the most improved site (our center-most observation site), while Daybreak was our least improved site (this was on the edge of our domain)

    - ➢ Likely due to a combination of factors including: smaller emissions, weaker spatiotemporal influence, limited emission uncertainty in this area

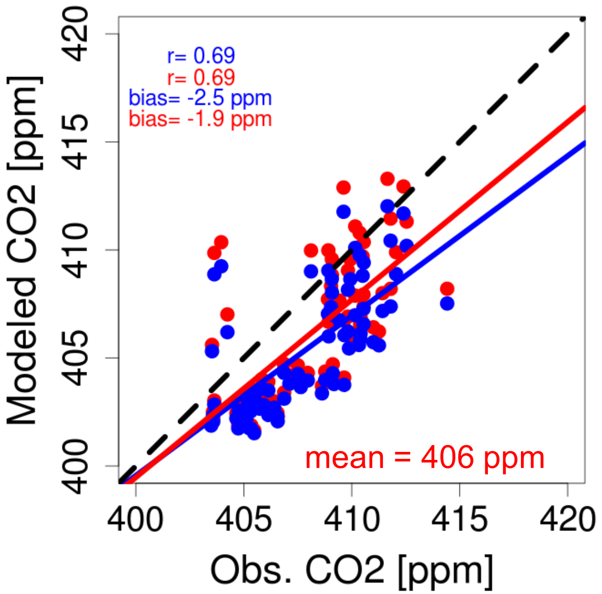




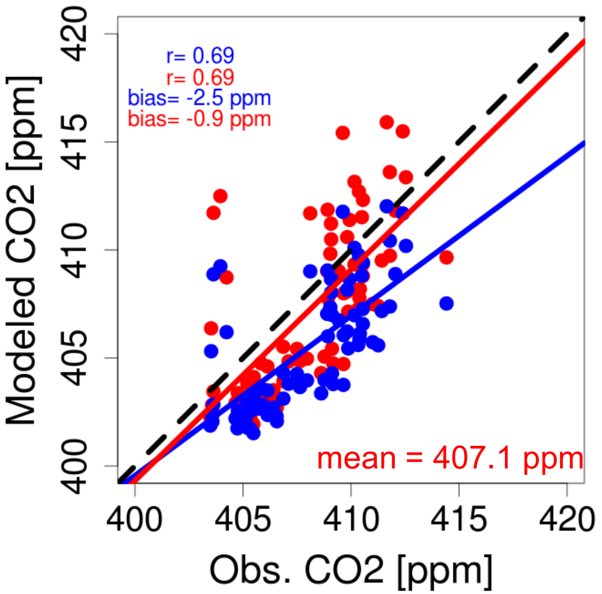
Using larger (4 ppm) measurement uncertainty to simulate corrections using a low-cost network

- Allows the inversion simulation to allocate emissions corrections to the SW Salt Lake Valley.
- It is unclear if this is "more accurate" or not. Further analysis is needed.

SUG only



SUG, DBK, RPK, WBB

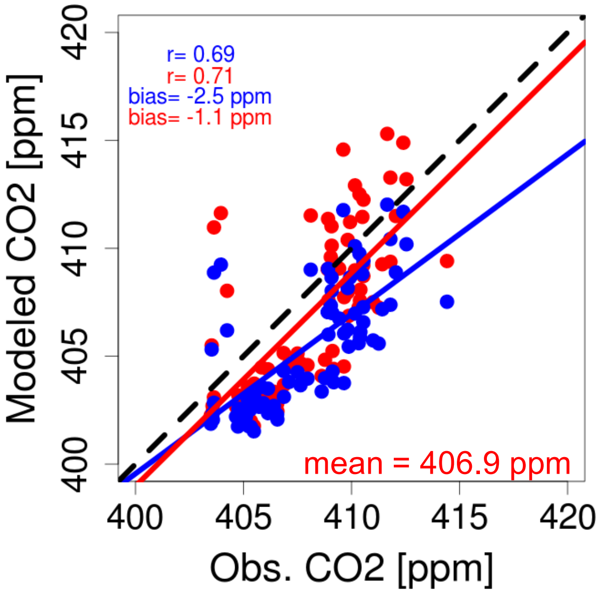


Red line comparison

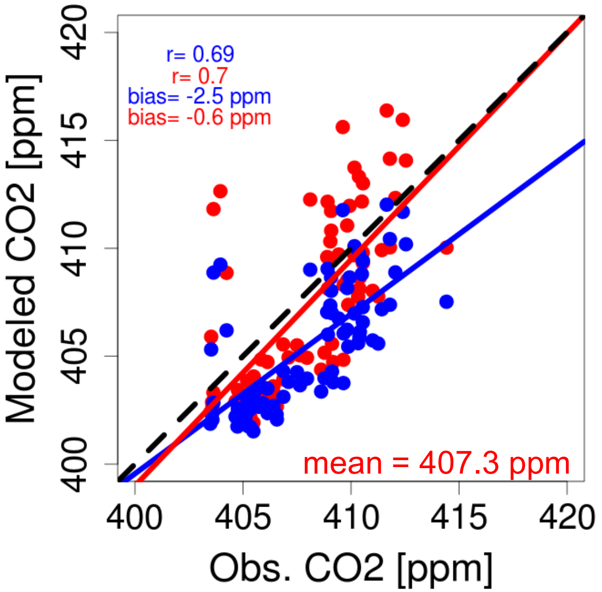
Obs. mean = 408.0 ppm

Prior mean = 405.5 ppm

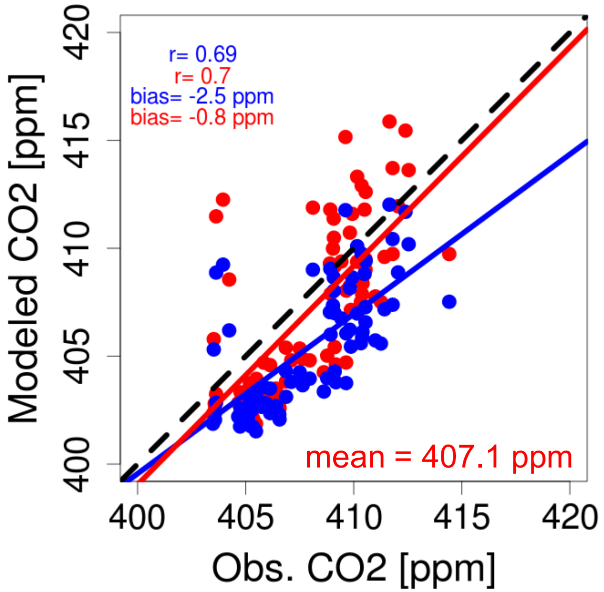
TRAX only



All observations



All obs. w/ 4 ppm uncertainty

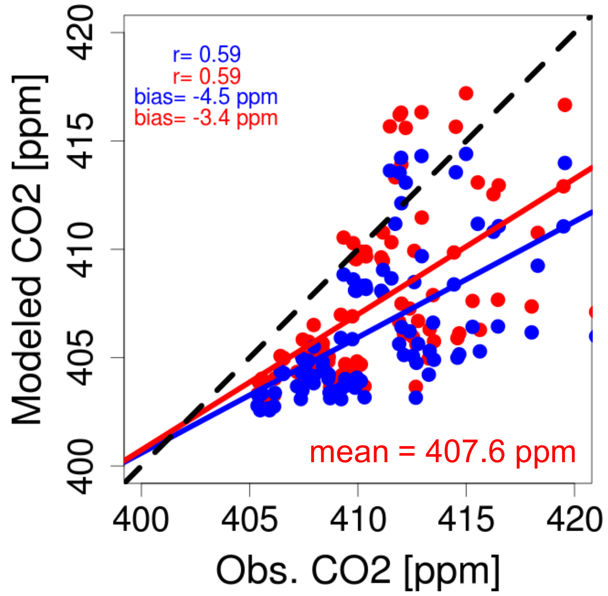


Green line comparison

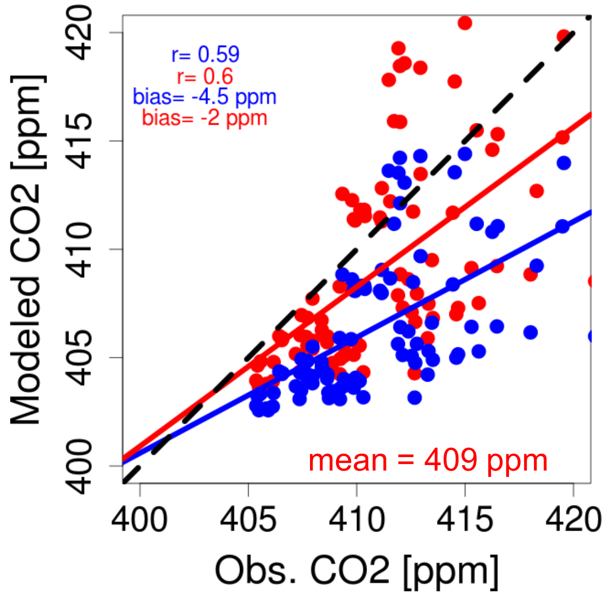
Obs. mean = 411.0 ppm

Prior mean = 406.5 ppm

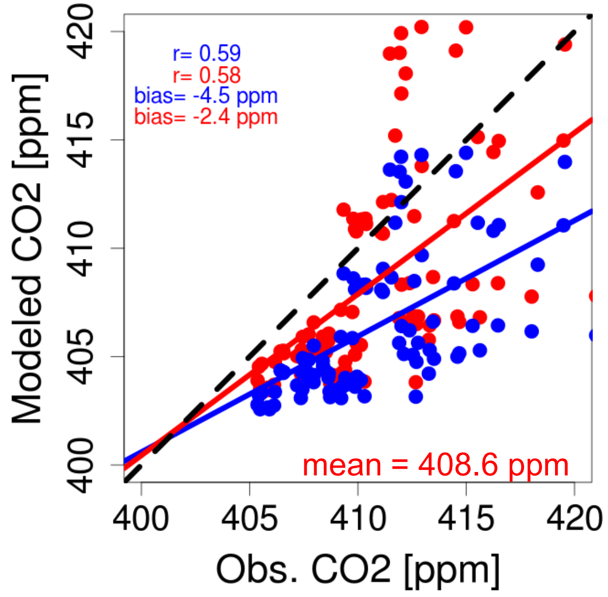
SUG only



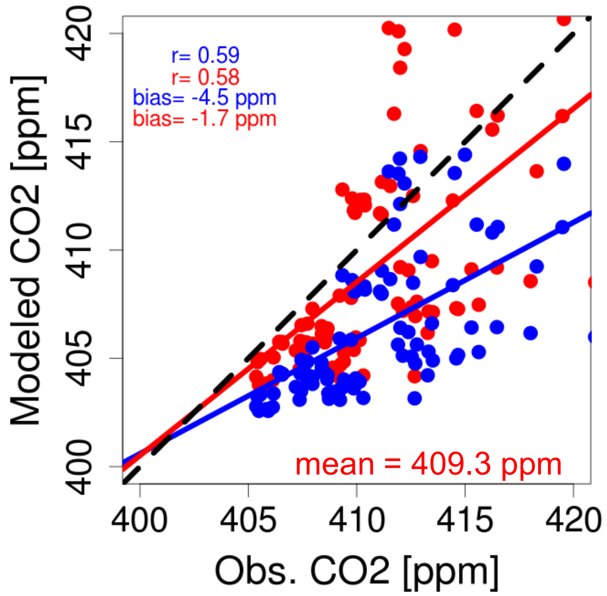
SUG, DBK, RPK, WBB



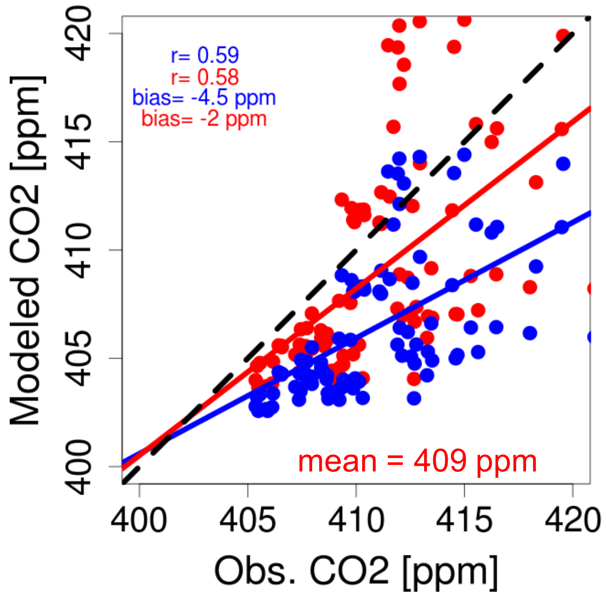
TRAX only



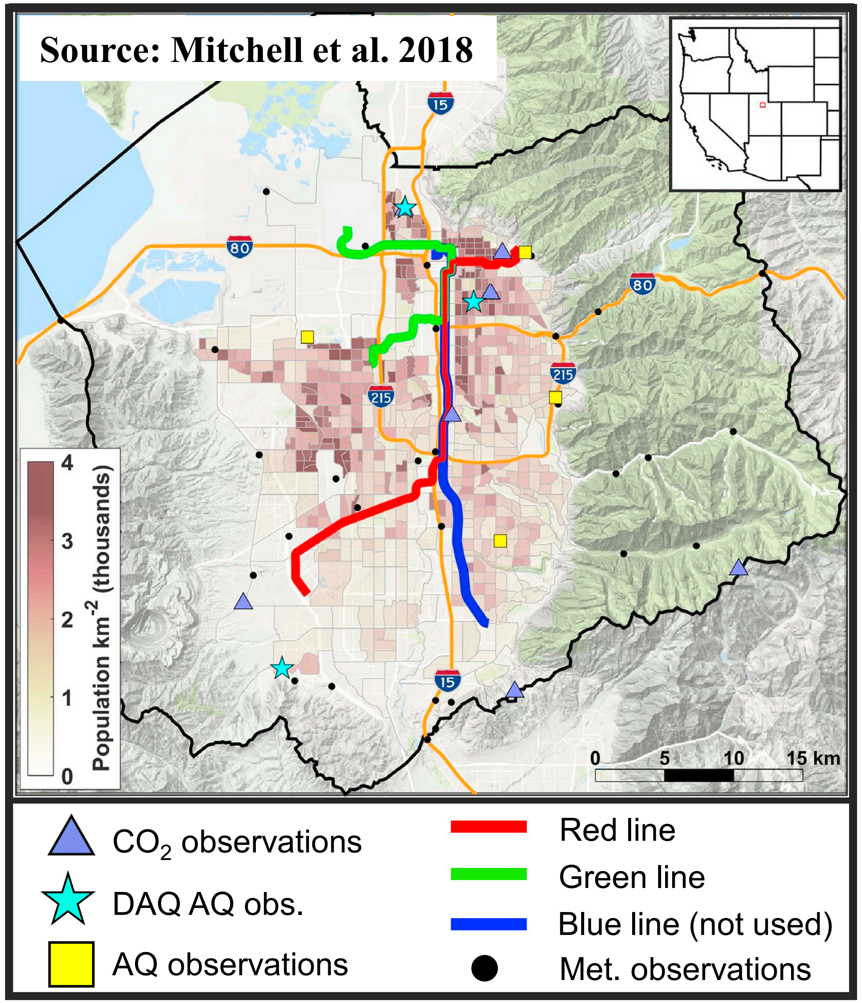
All observations

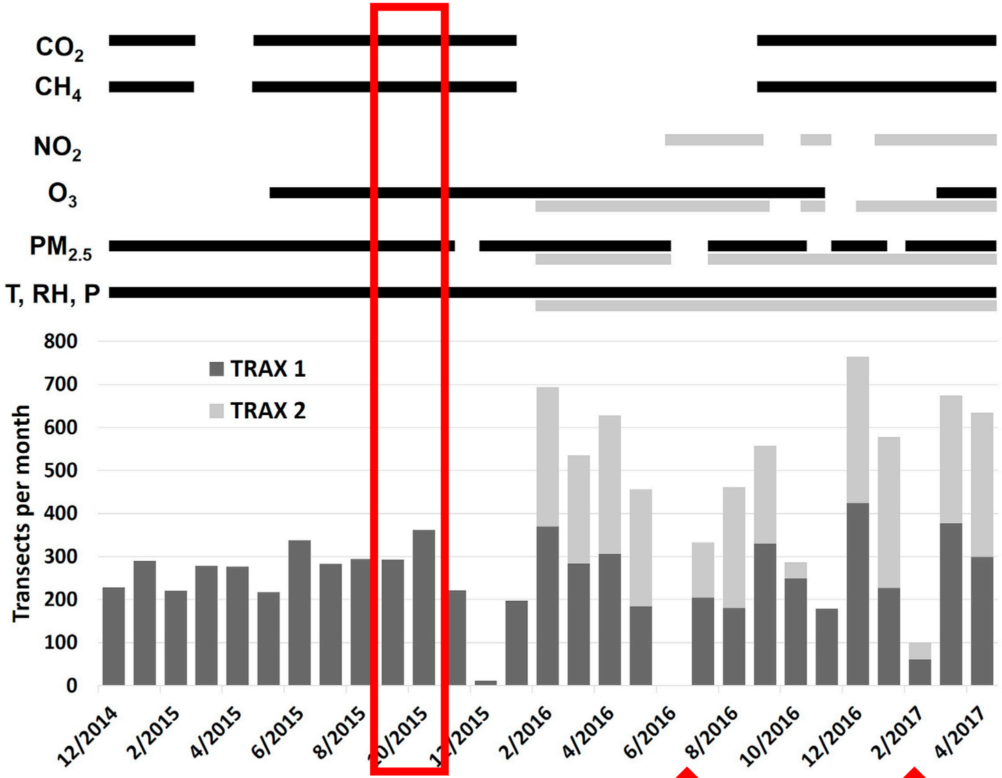


All obs. w/ 4 ppm uncertainty



Observations:

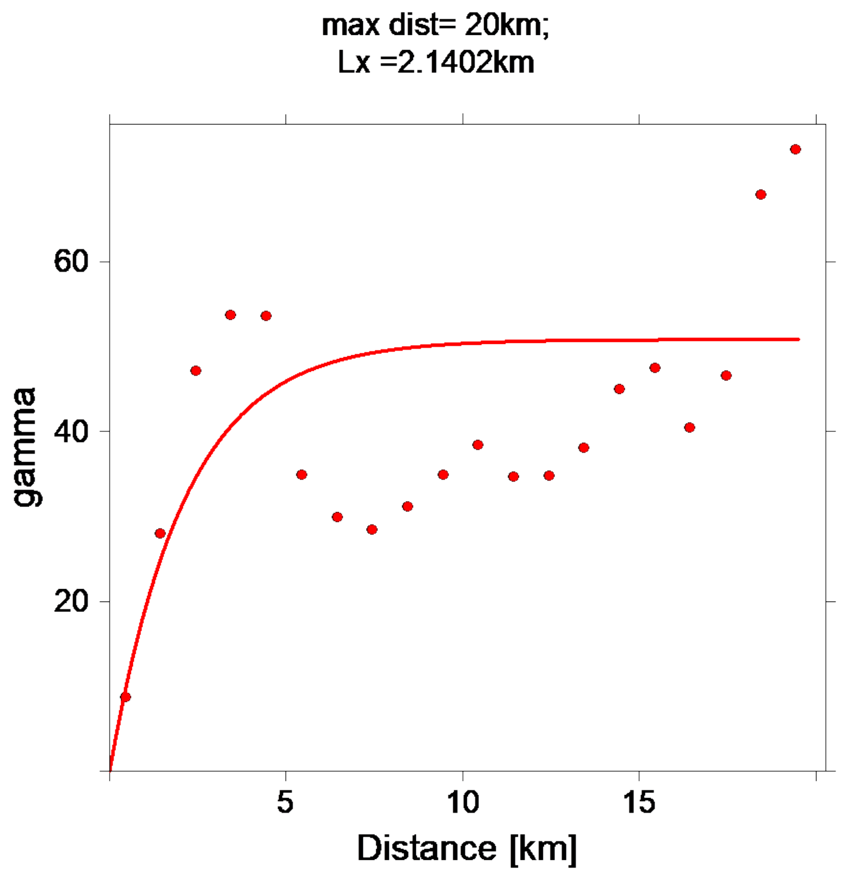




- Best data availability for CO_2 during the fall of 2015 for TRAX
  - Also wanted to pick a time where carbon fluxes from the biosphere are small, while also selecting a time period outside of cold-pool season
  - Only selected observations during the afternoon 18-23z (12-5:00 PM LST)

Lots of data associated with TRAX…!

- Each TRAX transect could consist of >1000 of more CO_2 measurements, with ~700 transects total, during the time of interest!
- As a result, we opted to bin the TRAX data; however, in order to determine the length of the bin, we had to run a variogram analysis on our TRAX data
- Variogram analysis indicated that an appropriate bin length = ~2.1-km



- The red line has a total length of ~40-km, thus we ended up with 20 bins (green line length = ~24-km, 12 bins)

Model Data Mismatch:

$$\hat{\mathbf{s}} = \mathbf{s}_p + (\mathbf{HQ})^T(\mathbf{HQH}^T + \mathbf{R})^{-1}(\mathbf{z} - \mathbf{Hs}_p)$$

$$R_i = R_{part} + R_{aggr} + R_{eddy} + R_{bg} + R_{transPBL} + R_{transWIND} + R_{ocean} + R_{instr} + R_{other?}$$

R_{part} = .1 ppm — Computed from trajectory analysis

R_{aggr} = 40% of the mean CO_2 enhancement

R_{eddy} = 0 ppm

R_{bg} = 1.9 ppm — Mean RMSE between HDP obs, HDP smoothed data, and modeled

R_{PBL} = 7% of the mean CO_2 enhancement — Lin and Gerbig (2005)

R_{trans} = 35% of the mean CO_2 enhancement — Computed from STILT transport error calculation following Lin and Gerbig (2005)

R_{bio} = 25% — From Doug Catherine's bio inventory

R_{instru} = .25 ppm + .25 ppm (for TRAX receptors)

Exciting new project mapping air pollution using Google Street View Cars!

1. Develop hyperlocal hotspot identification and emissions quantification using STILT.
2. Inverse analysis of emission inventories.
3. Development of air pollution exposure modeling using machine learning.

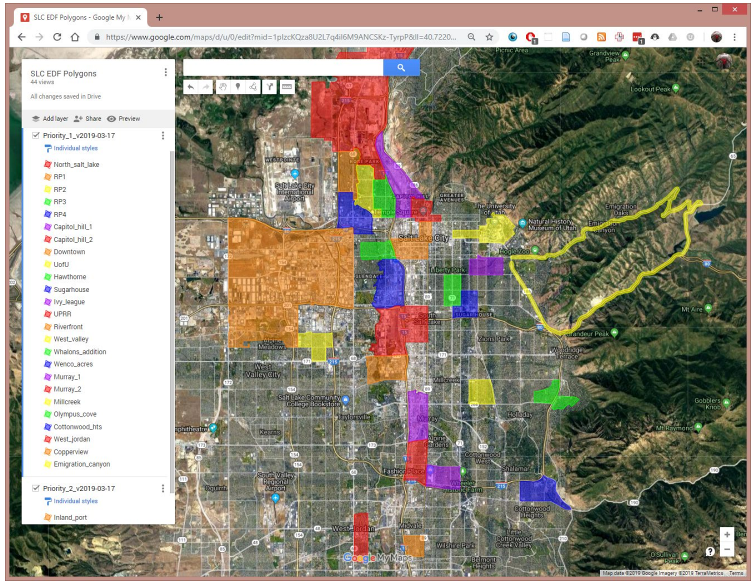
Targeted species:

CO_2, CH_4, CO, NO_x, $PM_{2.5}$, BC

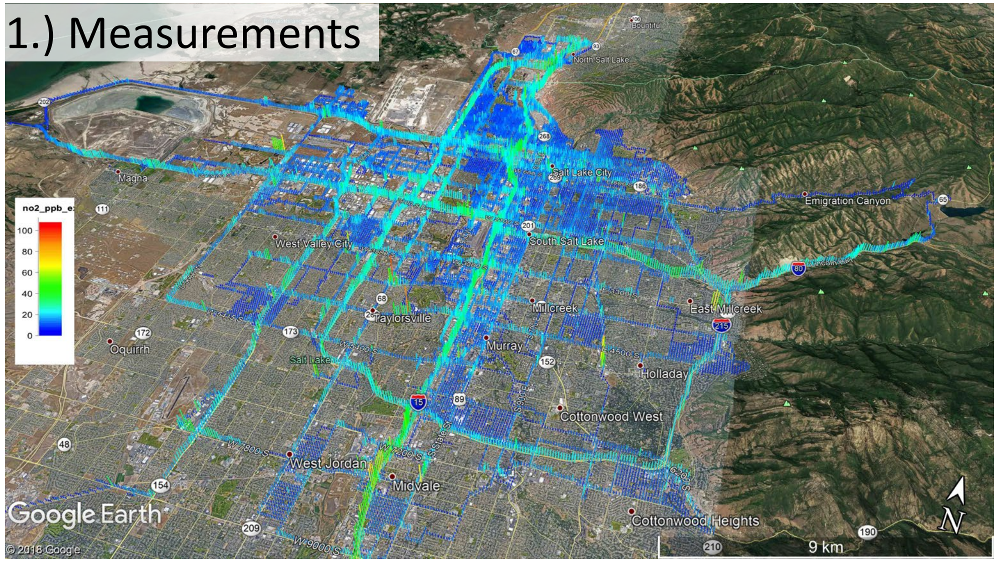
Google

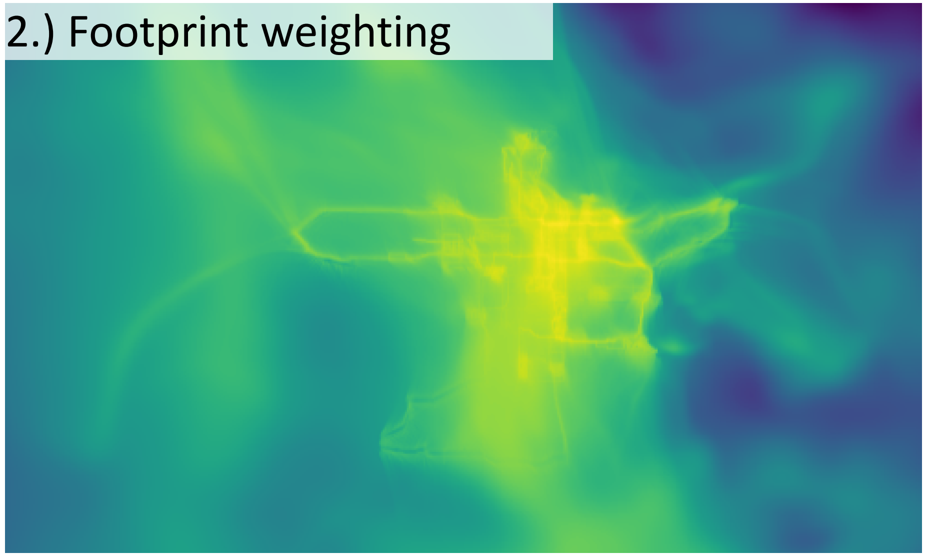
EDF ENVIRONMENTAL DEFENSE FUND®

Finding the ways that work

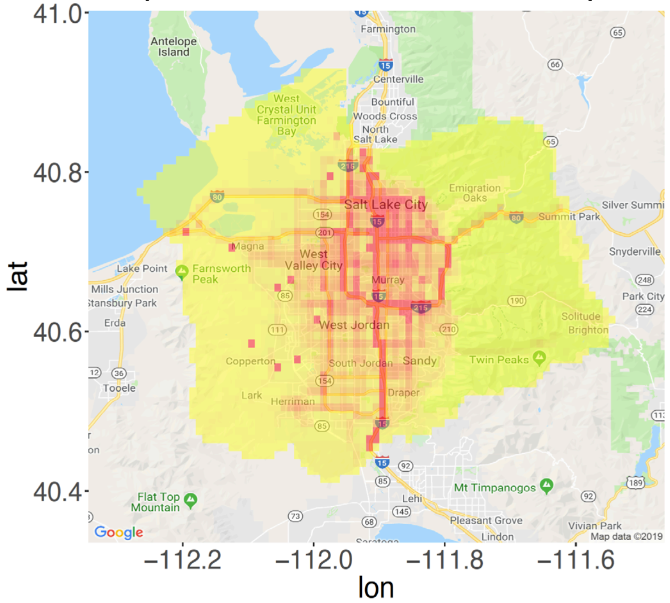


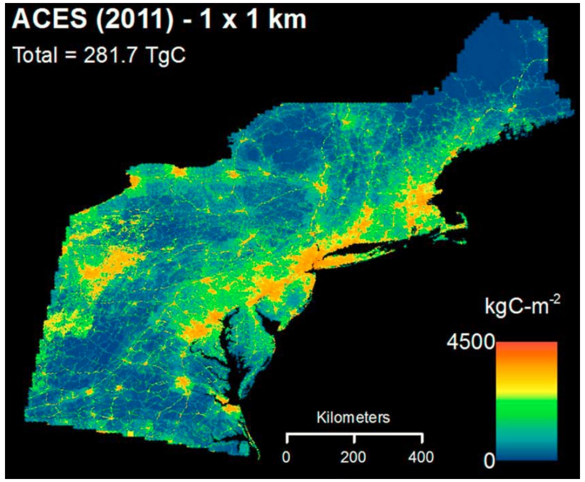
Hyperlocal source apportionment



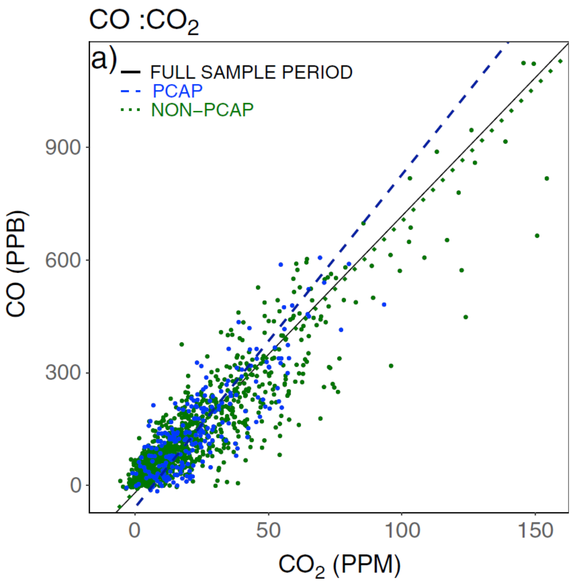


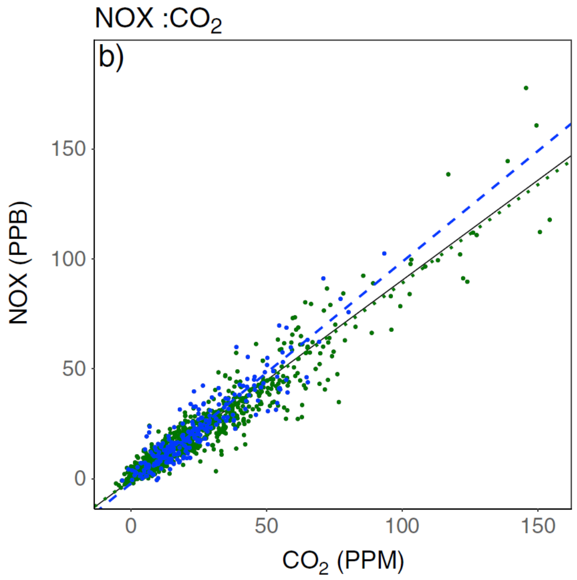
3.) Emission Inventories (Hestia + ACES v2)





4.) Concentration & emission ratios

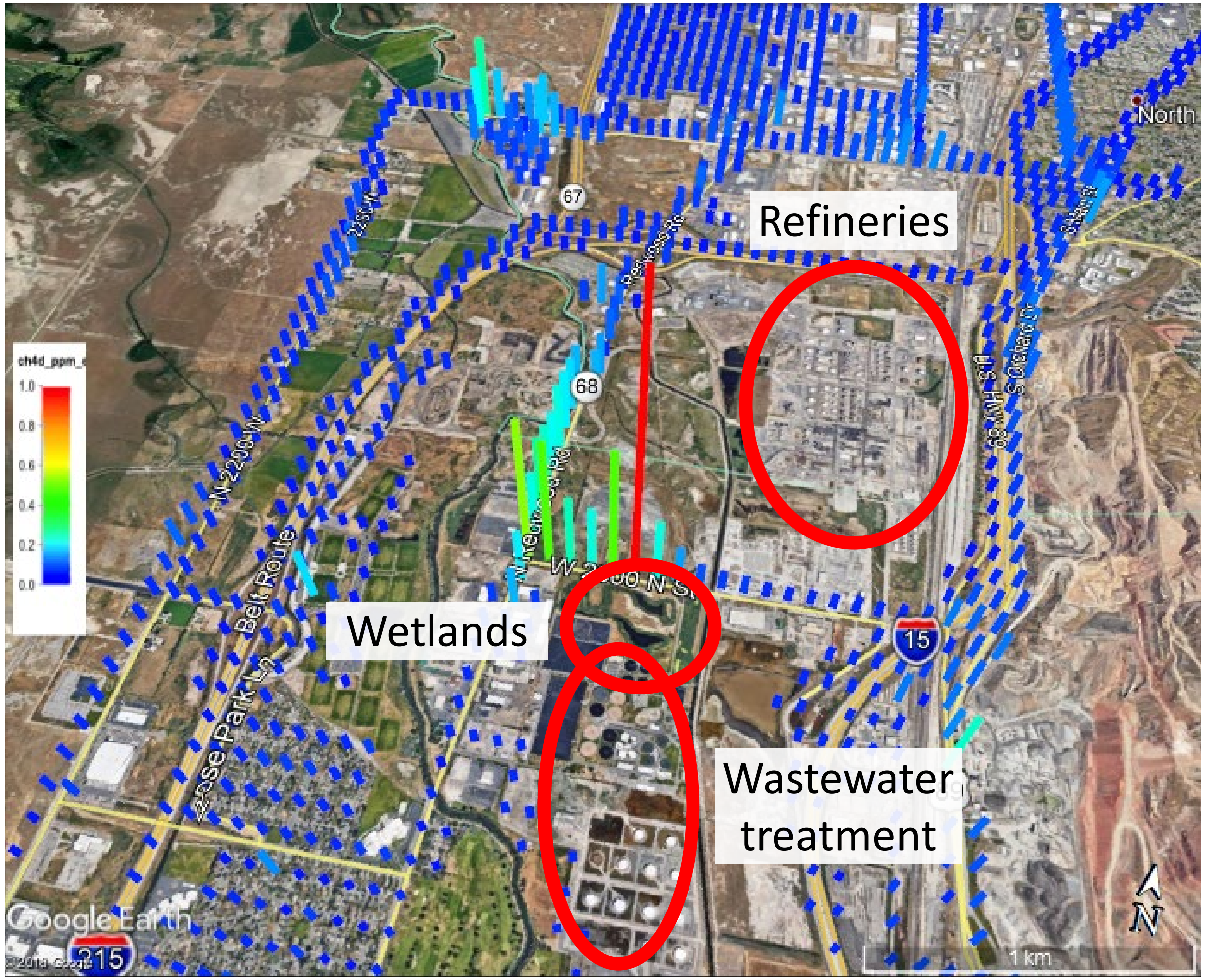


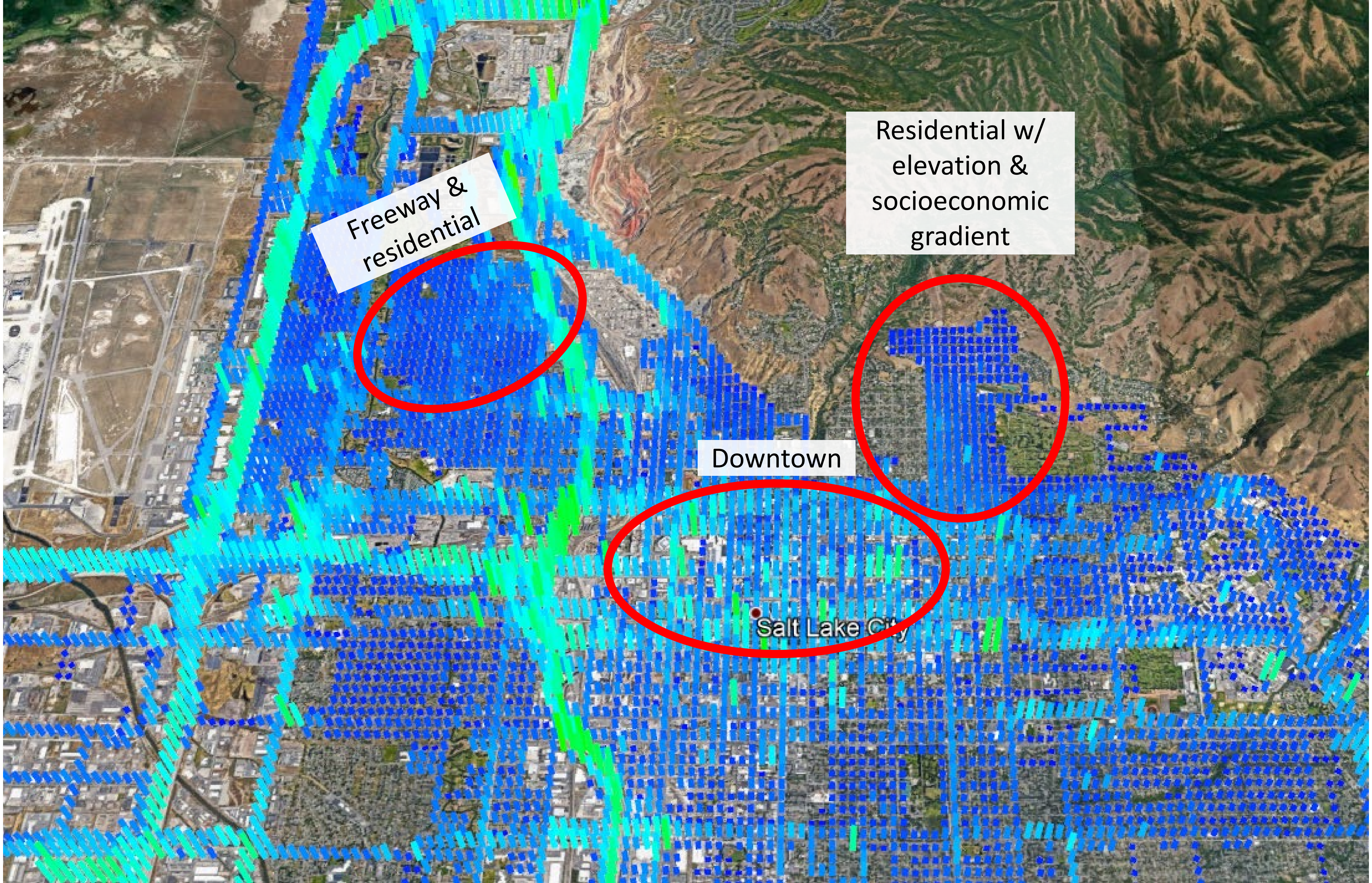


Hyperlocal source apportionment

Easy Cases:

Hard Cases:




Freeway & residential
Residential w/ elevation & socioeconomic gradient
Downtown
Salt Lake City