

ABSTRACT

The Bay area Environmental Air-quality & CO₂ Network (BEACO₂N) features a suite of gas and particulate sensors in shoebox-sized nodes located at ~2km resolution. There are ~70 nodes in the San Francisco Bay Area (Shusterman et al., 2016 and Figure 1) and are or will soon be deployments of 12-25 nodes in three other U.S. and two UK cities. Previous work has focused largely on the CO₂ dataset with analyses that describe network scale strategies for calibration and inverse models to map emissions at ~1km with hourly time resolution. Here we show spatial differences in CO and CO₂ reductions during the COVID-19 Shelter-in-Place order, highlighting the potential use BEACO₂N's CO dataset to constrain CO_2 emissions.



Figure 1. BEACO₂N nodes (blue) and reference instruments (red)

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Activity-based ("bottom-up") inventories for species like CO_2 large uncertainties associated. To combat this uncertainty we use surface-level measurements from BEACO₂N, coupled with meteorology, to update bottom-up priors of CO_2 and CO fluxes in the Bay Area. While CO is coemitted with CO_2 , $CO:CO_2$ ratios can vary with fuel-type and combustion process. Spatial differences in CO_2 and CO (and changes during Shelter-in-Place) provide insight into urban emissions of both species.

 CO_2 and CO were measured every 5-10 seconds at ~20 BEACO_2N locations throughout the Bay Area for the duration of the study period (February 2, 2020 - May 2, 2020). Hourly averages were taken for each node. For each measurement, 1000 hypothetical particle back-trajectories were generated using HRRR-STILT. Surface influence footprints were made for particle trajectories within half the boundary layer height. Footprints were used in a Bayesian inference framework to update a emissions priors according to

where x_a is the prior, H is the HRRR-STILT footprints, B is the prior error covariance matrix, R is the model-data mismatch error covariance matrix, y is the BEACO₂N measurements, and \hat{x} is the posterior fluxes at 1kmx1km resolution. The prior (x_a) and inversion infrastructure were adapted from Turner et al., 2020. The posterior was calculated for the 6 week period before the COVID-19 Shelter-in-Place order (2/2/2020 – 3/14/2020) and the 6 week period following the order (3/22/2020 – 5/2/2020). Resulting was averaged according to the time of day and compared with the hourly averages from Turner at al., 2020 (Figure 2).

Insights into Urban CO₂ and CO Emissions with BEACO₂N

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INTRODUCTION

METHODS

$\hat{\mathbf{x}} = \mathbf{x}_{a} + (\mathbf{HB})^{\mathsf{T}}(\mathbf{HBH}^{\mathsf{T}} + \mathbf{R})^{-1}(\mathbf{y}-\mathbf{Hx}_{a})$

Differences in Posterior fluxes of CO and CO₂ from the 6 week period before the COVID-19 Shelter-in-Place order (2/2/2020 – 3/14/2020) and the 6 week period following the order (3/22/2020 – 5/2/2020) are shown in Figure 2. A BEACO₂N region of influence was defined as the smallest area to contain 40% of HRRR-STILT footprints; fluxes outside the region of influence are hashed out. While CO₂ emissions decreased during Shelter-in-Place and anthropogenic decreases were largely localized to roads at night (1:00), morning (7:00), and evening (19:00), CO decreases were widely dispersed in the morning (7:00) and largely localized to roads in the evening (19:00). This spatial patten is speculated to be related to the importance of vehicle coldstart as a source of CO emissions.

Here we share results from a Bayesian inversion of CO measurements from $BEACO_2N$ towards spatially quantifying CO emissions in the Bay Area in February-April, 2020. We disaggregate this result by time of day and compare the emissions to Turner et al., 2020 to demonstrate the unique spatial pattern of CO emissions compared to CO_2 emissions. This result demonstrates the potential use of $CO:CO_2$ ratios to constrain CO_2 emissions, which will be explored further in future work.

RESULTS



Figure 2. Change in CO and CO₂ Fluxes During Shelter in Place by Time of Day

CONCLUSIONS



REFERENCES

Shusterman, A. A. *et al.* Observing local CO₂ sources using low-cost, near-surface urban monitors. *Atmospheric Chemistry and Physics* **18**, 13773–13785 (2018).

Turner, A. J. *et al.* Observed Impacts of COVID-19 on Urban CO2 Emissions. *Geophysical Research Letters* **47**, e2020GL090037 (2020).