Observed Impacts of COVID-19 on Urban CO2 Emissions

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Abstract Governments restricted mobility and effectively shuttered much of the global economy in response to the COVID-19 pandemic. Six San Francisco Bay Area counties were the first region in the United States to issue a “shelter-in-place” order asking non-essential workers to stay home. Here we use CO2 observations from 35 Berkeley Environment, Air-quality and CO2 Network (BEACO2N) nodes and an atmospheric transport model to quantify changes in urban CO2 emissions due to the order. We infer hourly emissions at 900-m spatial resolution for 6 weeks before and 6 weeks during the order. We observe a 30% decrease in anthropogenic CO2 emissions during the order and show that this decrease is primarily due to changes in traffic (–48%) with pronounced changes to daily and weekly cycles; non-traffic emissions show small changes (–8%). These findings provide a glimpse into a future with reduced CO2 emissions through electrification of vehicles.

Plain Language Summary This work uses atmospheric observations to quantify the changes in urban CO2 emissions from different sectors in response to COVID-19 mobility regulations.

1. Introduction

Carbon dioxide (CO2) is an atmospheric trace gas responsible for most of the growth in anthropogenic radiative forcing (IPCC, 2013). Mitigating long-term climate change necessitates drastic reductions to our CO2 emissions. Specifically, limiting global mean warming to 1.5°C requires reaching net-zero anthropogenic CO2 emissions by 2050 (IPCC, 2018). Over 70% of these anthropogenic CO2 emissions in the United States are attributable to urban areas (EIA, 2015; Hutyra et al., 2014); as such, it is important to be able to accurately quantify the emissions from these regions to support regulatory policies aimed at CO2 reduction and provide citizens with metrics indicating their effectiveness.

The abrupt shuttering of the global economy in response to the COVID-19 global pandemic presents an opportunity to evaluate methods for quantifying urban CO2 emissions, to assess our ability to attribute emissions to specific source sectors, and to describe the changes in emissions from different sectors. Understanding the changes that occurred during the COVID-19 period will allow us to identify (1) the magnitude and subset of CO2 emissions that respond to changes in our travel to/from workplaces on short time scales and (2) the sectors whose emissions persist irrespective of changes in urban travel patterns. Recent research used changes in activity data to predict the impact of COVID-19 on global CO2 emissions and inferred a ~17% (~11% to ~25%) change in global daily CO2 emissions (Le Quéré et al., 2020). This prediction has yet to be confirmed with measurements of atmospheric CO2.

The focus of this study is the San Francisco Bay Area in Northern California as it was the first region in the United States to enact regulations on mobility through a “shelter-in-place” (SIP) order on 16 March 2020 (Contra Costa County Health Officer, 2020). We use a dense network of CO2 observations across the north eastern region of the San Francisco Bay Area to quantify the impacts of the SIP order on urban CO2 emissions. Figure 1a shows the spatial coverage of our ground-based network of in situ sensors: the Berkeley Environmental Air-quality and CO2 Network (BEACO2N; Shusterman et al., 2016; Turner et al., 2016; Shusterman et al., 2018; Kim et al., 2018). Shusterman et al. (2016) and Text S1 give additional details on the
network. We examine data from the study period between 2 February 2020 and 2 May 2020, during which 35 sensors were operational.

2. Atmospheric Inversion Framework

Figure 2 shows a comparison of the network-wide median CO₂ concentrations for each day-of-week for 6 weeks before and during the SIP order. We observe a 5–50 ppm decrease in midweek CO₂ concentrations with the most pronounced changes on Monday through Thursday during the morning rush hour (~07:00 local time). Weekend concentrations show small differences in the median between the two time periods, although the variability is somewhat larger before the SIP. These observations suggest that (1) large reductions in CO₂ emissions occurred due to the SIP order and (2) marked changes to both the daily and weekly cycle of emissions due to shifts in human activity. Quantifying and attributing changes in CO₂ concentrations to emissions require accounting for the coupling of meteorology and emissions.

Figure 2. Weekly CO₂ concentrations before and during shelter-in-place order. Solid lines show the median across the BEACO₂N network and the shaded region indicates the 16th to 84th percentile. Purple shows 6 weeks of data before shelter-in-place (2 February 2020 through 14 March 2020) and green is 6 weeks during shelter-in-place (22 March 2020 through 2 May 2020). Blue/yellow background shading is based on cosine of the solar zenith angle with white indicating dawn and dusk.
We use the Stochastic Time-Inverted Lagrangian Transport model (STILT; Fasoli et al., 2018; Lin et al., 2003) with meteorology from the NOAA High-Resolution Rapid Refresh (HRRR Kenyon et al., 2016) to both estimate the sensitivity of each measurement to upwind emission sources and estimate the concentration upwind of our domain. Text S2 provides details on the transport modeling. Each measurement $y_i$ has a unique background concentration $\beta$, see Text S3 and footprint $h_i$. The footprint represents the spatiotemporal region that an atmospheric measurement is sensitive to (i.e., the region that could influence a measurement; see Fasoli et al., 2018; Lin et al., 2003; and Turner et al., 2016, 2018, for additional details on constructing the footprints).

The measurements are related to the surface CO$_2$ emissions $x$ as $y = h x + b$, and we use Bayesian inference to obtain hourly CO$_2$ emissions at 900-m spatial resolution from the atmospheric measurements. Prior fluxes are adapted from previous work (McDonald et al., 2014; Turner et al., 2016) but now use a biosphere derived from measurements of solar-induced chlorophyll fluorescence (SIF; Turner et al., 2020). Additionally, we manually inspected the 20 largest point sources to ensure they were spatially allocated to plausible locations. Errors are assumed to be Gaussian and include off-diagonal terms in both error covariance matrices. Following Rodgers (1990), we solve for the hourly posterior fluxes at 900-m spatial resolution as

$$ \hat{x} = x_0 + (HB)^T (HBH^T + R)^{-1} (y - Hx_0) $$

where $\hat{x}$ is the posterior fluxes, $x_0$ is the prior emissions, $y$ is the BEACO2N observations, $H$ is the matrix of footprints from HRRR-STILT, $R$ is the model-data mismatch error covariance matrix, and $B$ is the prior error covariance matrix (see Text S4 for additional details).

Posterior fluxes will reflect the prior fluxes in regions with low sensitivity from the measurements. This can be clearly seen by looking at Equation 1 and the gain matrix: $G = (HB)^T (HBH^T + R)^{-1}$. We can see that $\hat{x} \rightarrow x_0$ in Equation 1 as $G \rightarrow 0$, indicating that our posterior solution will not deviate from the prior in regions of low sensitivity. As such, we focus our study on regions with high sensitivity because those are the regions that our observations can robustly constrain. Figure 1b shows the region of influence for the BEACO2N network. We find the network to be most sensitive to the eastern portion of the San Francisco Bay Area with upwind influence extending east across the bay to San Francisco. The white contour in Figure 1b encapsulates the top 40% of the total of the network sensitivity, hereafter referred to as the “BEACO2N Domain,” where we expect strong constraints from the measurements.

### 3. High-Resolution Posterior Fluxes

The resulting posterior fluxes inferred using BEACO2N observations are shown in Figure 3. Figures 3a and 3b show the spatial patterns before and during the SIP order, respectively, while Figure 3c shows the difference. Changes on roadways are evident in the pattern of differences. Changes to other sectors are more subtle. We have high confidence in the fluxes within the BEACO2N Domain because this is the region where the BEACO2N network is strongly sensitive to; fluxes outside of this region will revert to the prior emissions. Two spatial features that immediately stand out in Figure 3c are a 0.4 tC km$^{-2}$ hr$^{-1}$ decrease in emissions over urban areas within the BEACO2N Domain and a modest decrease (0.15 tC km$^{-2}$ hr$^{-1}$) across most of the San Francisco Bay Area. We are able to attribute these observed changes to particular sectors because of the (1) high spatial resolution obtained here, (2) satellite observations to constrain the biosphere, and (3) detailed prior information available in the region. We find that the modest regional decrease is due to the biosphere and the large changes in urban areas are predominantly due to decreases in traffic.

Estimating CO$_2$ fluxes from observations during spring is complicated by the onset of photosynthesis which results in a decrease in atmospheric concentrations. In Northern California, this begins with the grasslands and chaparral in land surrounding the urban core. As mentioned above, we use high-resolution satellite observations of SIF from TROPOMI to constrain the biospheric activity during this time of year (Turner et al., 2020), which have been shown to correlate strongly with photosynthetic activity (e.g., Frankenberg et al., 2011; Yang et al., 2015; and others). These space-borne SIF measurements indicate a 170% (37 tC/hr) increase in daytime CO$_2$ uptake from the biosphere across the BEACO2N Domain when comparing before and during the SIP order. This increase in biospheric activity inferred from space-borne SIF measurements drives the regional decrease in CO$_2$ fluxes shown in Figure 3c.
Figure 3. Spatial patterns of CO₂ fluxes in the San Francisco Bay Area. Panel (a) shows the average CO₂ fluxes for 6 weeks before shelter-in-place (2 February 2020 through 14 March 2020). Panel (b) shows the average over 6 weeks during shelter-in-place (22 March 2020 through 2 May 2020). Panel (c) is the difference. Black contour in all panels encompasses the top 40% of the total network influence (BEACO₂N Domain). Cross hatching indicates regions with low sensitivity to the BEACO₂N nodes.

The large changes within the BEACO₂N Domain coincide with major freeways in the San Francisco Bay Area. In particular, the largest decreases are observed over Interstate 880 (I-880) that runs north–south from San Jose to Oakland. Our observational network is only sensitive to the northern half of I-880, but the entirety of that section shows decreases in CO₂ fluxes in excess of 0.4 tC km⁻² hr⁻¹. I-880 is a crucial freeway for workers commuting to San Francisco. Other freeways that serve commuters also show large decreases in CO₂ fluxes (e.g., Interstates 80 and 580).

Figure 4 shows the posterior CO₂ emissions within the BEACO₂N Domain before and during the SIP order. In toto, we observe a 39% decrease in CO₂ fluxes between the two time periods. However, the most striking feature is the large perturbation to both the daily and weekly cycle of CO₂ fluxes. We observe large CO₂ fluxes that are coincident with rush hour before the SIP order. These features are largely absent during the SIP order. The pronounced changes in the daily cycle found here highlight the importance of incorporating measurements over the course of the day, rather than just the well-mixed afternoon as is often done.

A common method of characterizing errors in flux inversions is to examine the posterior error covariance matrix: $\mathbf{Q} = (\mathbf{H}^\top \mathbf{R}^{-1} \mathbf{H} + \mathbf{B}^{-1})^{-1}$. However, $\mathbf{Q}$ would have in excess of $10^{13}$ elements here and, assuming single precision, require more than 180 Tb to store. As such, $\mathbf{Q}$ is computationally intractable. We instead adopt two methods of characterizing the uncertainty: (1) examination of the day-to-day variation and (2) k-fold cross validation. The shaded regions in Figure 4 show the 1-σ spread in CO₂ fluxes for given hour of the week (i.e., the variation across the 6 weeks). The cross validation is shown in Text S7 where we find the posterior fluxes to explain 23% more variability than the prior fluxes when compared against observations withheld from the flux inversion. There is ongoing work comparing these results against independent data of traffic flow from the California Department of Transportation (Caltrans, 2020).

In our work, we solve for total CO₂ fluxes. However, we leverage the high spatial resolution obtained here to partition our posterior CO₂ fluxes to specific sectors because sources spatially separate as the resolution increases. For example, McDonald et al. (2014) demonstrated that 1-km spatial resolution was necessary to distinguish freeways from arterial roads. Here, we classify grid cells that have the majority of prior emissions coming from a single sector (e.g., we classify a grid cell as “traffic” if more than 50% of the prior emissions come from the traffic sector; see Text S5 for more details).

Figure 4 attributes the posterior CO₂ emissions within the BEACO₂N Domain to three sectors: (1) vehicle traffic, (2) stationary anthropogenic emissions, and (3) biogenic. Over 80% of the emissions from the stationary sector are due to the industrial point sources which likely have small variations over the diurnal cycle. We observe the highest CO₂ emissions during the morning rush hour in the middle of the week. This peak is only present during the weekdays. Daily average emissions increase from Sunday to their maximum on Wednesday and then decrease from Wednesday to Saturday. In contrast, daily average emissions during SIP have more subtle differences between weekdays and weekends, as suggested by the day of week variation in the concentrations of CO₂ shown in Figure 2. Weekday emissions start earlier than on weekends before and after the SIP order. After the SIP, rush hour emissions are lower, but they still extend emissions earlier and later than seen on weekends, resulting in a flatter weekday daytime emissions profile than on weekends.
We find that grid cells classified as stationary sources decreased by 8% (−14 tC/hr) in response to the SIP order. The posterior emissions indicate a small diurnal cycle in the stationary sector that is largely absent before the SIP order and is not present in the prior emissions. In contrast, we find a −48% change (−97 tC/hr) in the weekly average CO₂ emissions from grid cells that are classified as freeway whereas emissions. Emissions from vehicles at night pre-SIP averaged ≈154 tC/hr and during SIP the nighttime emissions averaged ≈55 tC/hr. This represents a 64% decrease in nighttime emissions and a 40% decrease during daytime (240 to 144 tC/hr). Independent data from the California Department of Transportation also indicate a 41% and 34% decrease in vehicle miles traveled by cars and trucks, respectively, for road segments in the BEACO₂N Domain (Caltrans, 2020).

On weekdays before the SIP order, vehicles are the largest source of CO₂ during daytime, while on pre-SIP weekends, stationary and traffic sources have a comparable magnitude. After the SIP order, stationary sources are generally the largest term. Such sectoral changes are possible to observe here due to the densely spaced nodes in the BEACO₂N network, allowing us to obtain subkilometer spatial resolution and resolve different sectors.

4. Conclusions

This unnatural experiment conducted in response to COVID-19 has demonstrated the subset of CO₂ emissions that are elastic and those that are more entrenched. Emissions from traffic are highly elastic and could be rapidly mitigated in response to either technological advances or regulations. In contrast, the stationary
emissions (e.g., industrial point sources and residential heating) showed minimal changes in response to the SIP order. This implies that those sources are more entrenched and will require longer time scales to mitigate if we hope to limit future warming. These findings provide a glimpse into a future where CO₂ emissions from vehicle traffic are reduced through the electrification of the vehicle fleet, which would also have air quality co-benefits; observing these CO₂ emission changes from such a transition will require sustained measurements as the changes will be more subtle than the abrupt 48% changes seen here.

Conflict of Interest
The authors declare no competing interests.

Data Availability Statement
CO₂ data are available online (http://beacon.berkeley.edu/). Code has been deposited in GitHub (https://www.github.com/alexjturner/UrbanInversion).

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References