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 28% decrease in anthropogenic CO2 emissions during the order and show this decrease is primarily due to changes in traffic (-44%) 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. (submitted to GRL: 2020-07-24 16:49:19)

Observed impacts of COVID-19 on urban CO_2 emissions

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Key Points:

- Observe a 28% decrease in urban CO_2 emissions from the San Francisco Bay Area in response to COVID-19 mobility restrictions
- Changes are primarily driven by a decrease in CO_2 emissions from traffic (-44%)
- Large change to the weekly and diurnal cycle of emissions with reductions in morning rush-hour 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 CO_2 observations from 35 Berkeley Environment, Air-quality and CO_2 Network (BEACO_2N) nodes and an atmospheric transport model to quantify changes in urban CO_2 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 28% decrease in anthropogenic CO_2 emissions during the order and show this decrease is primarily due to changes in traffic (-44%) 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 CO_2 emissions through electrification of vehicles.

Plain Language Summary

This work uses atmospheric observations to quantify the changes in urban CO_2 emissions from different sectors in response to COVID-19 mobility regulations.

1 Introduction

Carbon dioxide (CO_2) 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 CO_2 emissions. Specifically, limiting global mean warming to 1.5°C requires reaching net-zero anthropogenic CO_2 emissions by 2050 (IPCC, 2018). Over 70% of these anthropogenic CO_2 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 CO_2 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 CO_2 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 CO_2 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 CO_2 emissions and inferred a -17% (-11% to -25%) change in global daily CO_2 emissions (Le Quéré et al., 2020). This prediction has yet to be confirmed with measurements of atmospheric CO_2.

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 March 16, 2020 (Contra Costa County Health Officer, 2020). We use a dense network of CO_2 observations across the north eastern region of the San Francisco Bay Area to quantify the impacts of the SIP order on urban CO_2 emissions. Figure 1A shows the spatial coverage of our ground-based network of *in situ* sensors: the Berkeley Environmental Air-quality & CO_2 Network (BEACO_2N; Shusterman et al., 2016; Turner et al., 2016; Kim et al., 2018; Shusterman et al., 2018). We examine data from the study period between February 2, 2020 and May 2, 2020, during which 35 sensors were operational.

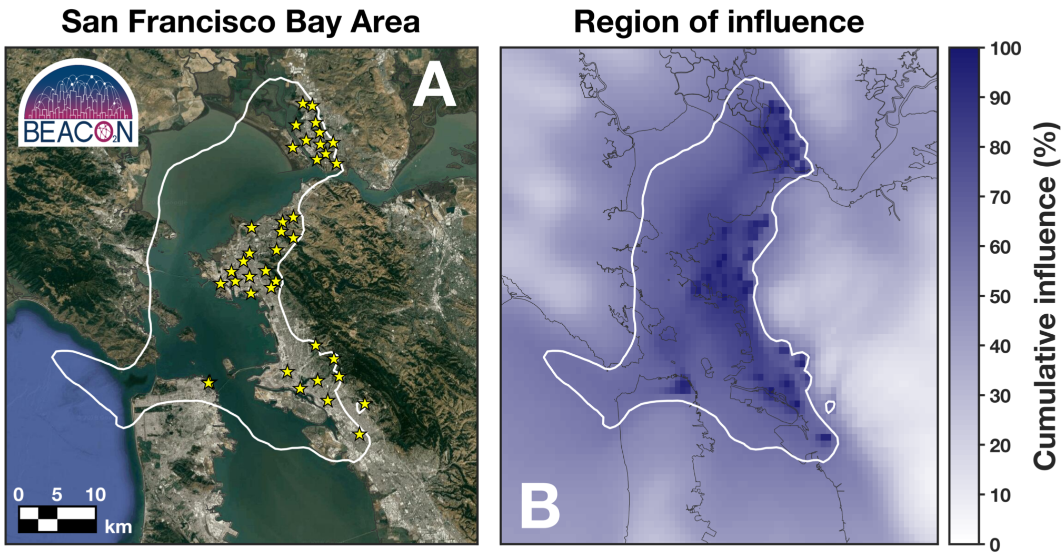

Figure 1. Observational network in the San Francisco Bay Area. Panel A shows the location of instruments in the Berkeley Environmental Air-quality & CO_2 Network (BEACO$_2$N; yellow stars). Panel B shows the cumulative influence to the network derived from STILT footprints for observations in March 2020. White contour in both panels indicates the region that contains the largest 40% of the total network influence (referred to as the "BEACO$_2$N Domain").

2 Atmospheric Inversion Framework

Figure 2 shows a comparison of the network-wide CO_2 concentrations averaged for each day-of-week for six weeks before and during the SIP order. We observe a 5-50 ppm decrease in mid-week CO_2 concentrations with the most pronounced changes on Monday through Thursday during the morning rush-hour ($\sim$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: 1) large reductions in CO_2 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 CO_2 concentrations to emissions requires accounting for the coupling of meteorology and emissions.

We use the Stochastic Time-Inverted Lagrangian Transport model (STILT; Lin et al., 2003; Fasoli et al., 2018) 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. Each measurement (y_i) has a unique surface sensitivity ($\mathbf{h}_i$) and background concentration (b_i). The measurements are related to the surface CO_2 emissions ($\mathbf{x}$) as: $y_i = \mathbf{h}_i\mathbf{x} + b_i$ 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 (Turner et al., 2016; McDonald et al., 2014) 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:

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

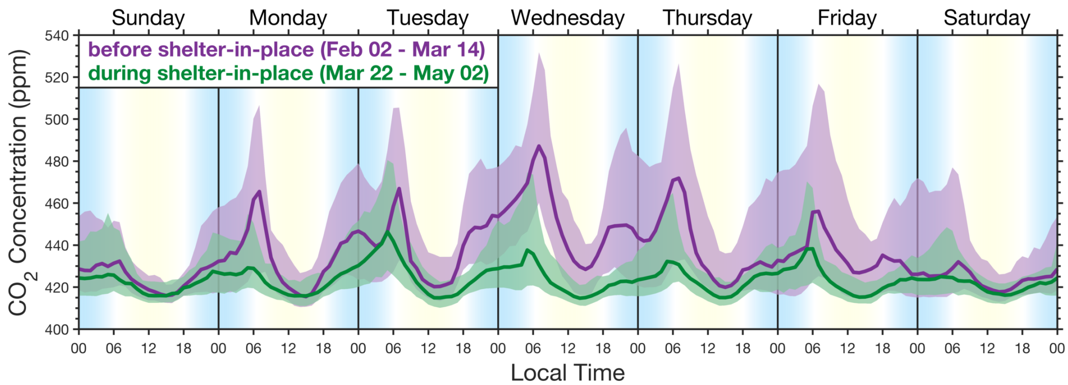

Figure 2. Weekly CO_2 concentrations before and during shelter-in-place order. Solid lines show the median across the BEACO$_2$N network and the shaded region indicates the 16$^{\text{th}}$ to 84$^{\text{th}}$ percentile. Purple shows 6 weeks of data before shelter-in-place (February 2, 2020 through March 14, 2020) and green is 6 weeks during shelter-in-place (March 22, 2020 through May 2, 2020). Blue/yellow background shading is based on cosine of the solar zenith angle with white indicating dawn and dusk.

where $\hat{\mathbf{x}}$ $(m \times 1)$ is the posterior fluxes, $\mathbf{x_a}$ $(m \times 1)$ is the prior emissions, $\mathbf{y}$ $(n \times 1)$ is the BEACO$_2$N observations, $\mathbf{H}$ $(n{\times}m)$ is the matrix of footprints from HRRR-STILT, $\mathbf{R}$ $(n \times n)$ is the model-data mismatch error covariance matrix, and $\mathbf{B}$ $(m \times m)$ is the prior error covariance matrix (see Supplemental Section 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 the gain matrix $\mathbf{G} = (\mathbf{HB})^T \left(\mathbf{HBH}^T + \mathbf{R}\right)^{-1}$ and Eq. 1. We can see that $\hat{\mathbf{x}} \rightarrow \mathbf{x_a}$ in Eq. 1 as $\mathbf{G} \rightarrow \mathbf{0}$, 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 BEACO$_2$N 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 "BEACO$_2$N Domain", where we expect strong constraints from the measurements.

3 High Resolution Posterior Fluxes

The resulting posterior fluxes inferred using BEACO$_2$N observations are shown in Figure 3. Figs. 3A and 3B show the spatial patterns before and during the shelter-in-place order, respectively, while Fig. 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 BEACO$_2$N Domain because this is the region the BEACO$_2$N network is strongly sensitive to, fluxes outside of this region will revert to the prior emissions. Two spatial features that immediately stand out in Fig. 3C are: a 0.4 tC km^{-2} hr^{-1} decrease in emissions over urban areas within the BEACO$_2$N 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.

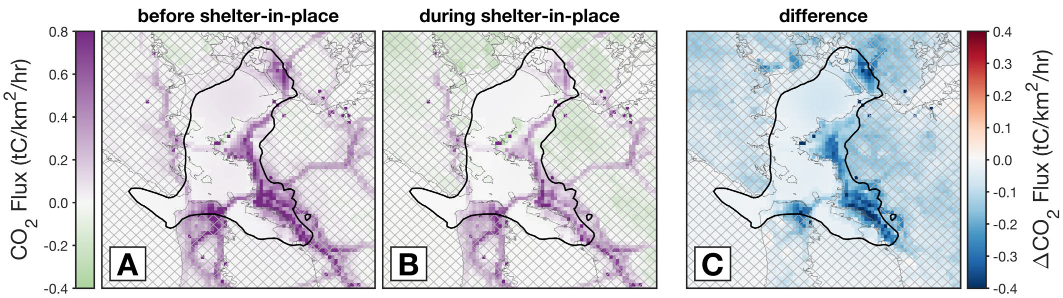

Figure 3. Spatial patterns of CO_2 fluxes in the San Francisco Bay Area. Panel A shows the average CO_2 fluxes for 6-weeks before shelter-in-place (February 2, 2020 through March 14, 2020). Panel B shows the average over 6-weeks during shelter-in-place (March 22, 2020 through May 2, 2020). Panel C is the difference. Black contour in all panels is the 60$^{\text{th}}$ percentile of total network influence (BEACO_2N Domain). Cross hatching indicates regions with low sensitivity to the BEACO_2N nodes.

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 to constrain the biospheric activity during this time of year (see 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 252% (26 tC/hr) increase in daytime CO_2 uptake from the biosphere across the BEACO_2N 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.

The large changes within the BEACO_2N 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 CO_2 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 CO_2 fluxes (e.g., Interstates 80 and 580).

We leverage the high spatial resolution obtained here to partition our posterior CO_2 fluxes to specific sectors because sources spatially separate as the resolution increases. For example, McDonald et al. (2014) demonstrated that 1-kilometer 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 Supplemental Section S5 for more details.

Figure 4 attributes the posterior CO_2 emissions within the BEACO_2N Domain to three sectors, 1) vehicle traffic, 2) industrial point sources, home heating, and other non-vehicle related anthropogenic emissions, and 3) biogenic. On weekdays before the SIP order, vehicles are the largest source of CO_2 during daytime, while on pre-SIP weekends "other anthropogenic" are the largest daytime source. After the SIP order, "other anthropogenic" is always the largest source. We observe the highest CO_2 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 CO_2 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. Emissions from vehicles at night pre-SIP averaged $\sim$150 tC/hr and during SIP the nighttime emissions averaged $\sim$60 tC/hr. This represents a 61% decrease in nighttime emissions and a 39% decrease during daytime (245 to 157 tC/hr).

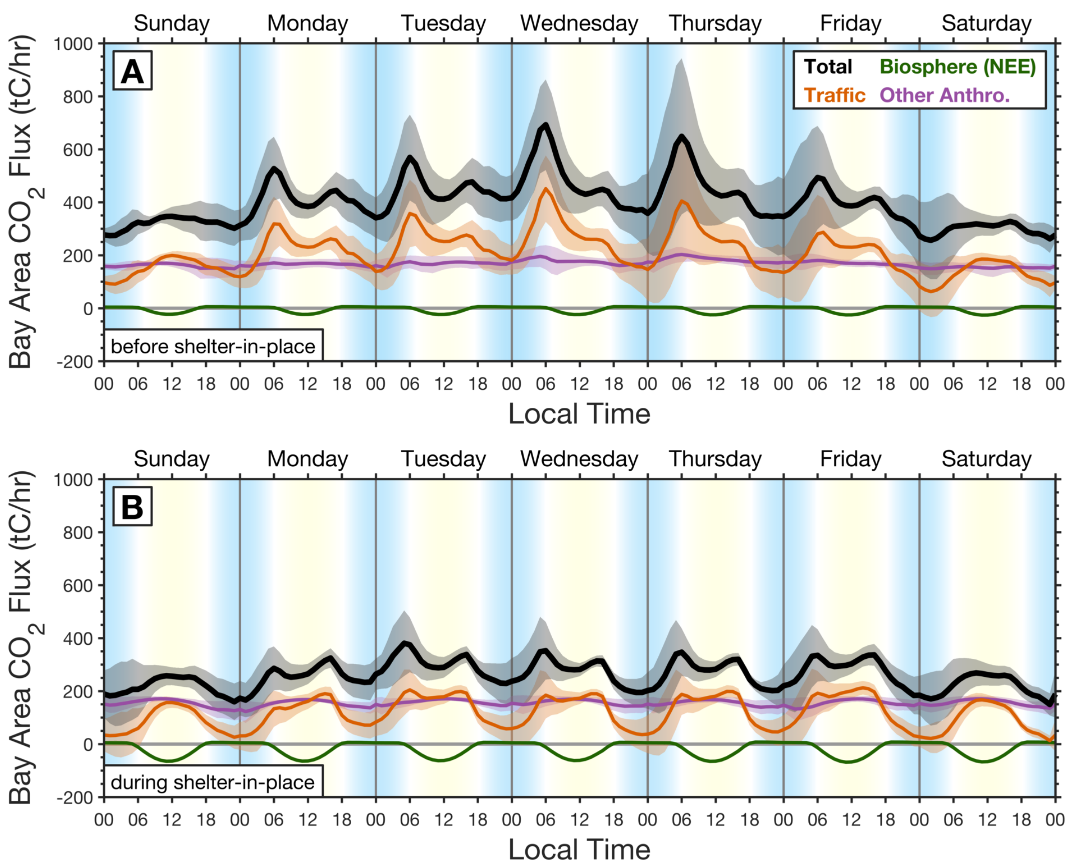

Figure 4. Weekly cycle of CO_2 fluxes before and during shelter-in-place order. Solid lines are the weekly mean CO_2 fluxes over the BEACO$_2$N Domain (40$^{\text{th}}$ percentile shown in Fig. 1) and shading is 1-σ. Black are the total fluxes. Orange are the traffic emissions. Purple are other anthropogenic emissions: industrial point sources, residential heating, and other non-vehicle anthropogenic sources. Green are the biosphere fluxes (Net Ecosystem Exchange; NEE). Panel A shows emissions before shelter-in-place (February 2, 2020 through March 14, 2020) and panel B shows emissions during shelter-in-place (March 22, 2020 through May 2, 2020).

We find a -44% change (-91 tC/hr) in the weekly average CO_2 emissions from grid cells that are classified as freeway whereas emissions from non-traffic anthropogenic sources ("Other Anthro." in Figure 4) only decreased by 8% (-13 tC/hr). Much of this decrease in non-traffic anthropogenic sources occurs at night. Independent data from the California Department of Transportation also indicates a 41% and 34% decrease in vehicle miles traveled by cars and trucks, respectively, for road segments in the BEACO$_2$N Domain (Caltrans, 2020). The posterior emissions indicate a small diurnal cycle in this sector that is largely absent before the SIP order and is not present in the prior emissions. Such sectoral changes are possible to observe here due to the densely spaced nodes in the BEACO$_2$N network, allowing us to obtain sub-kilometer spatial resolution and resolve different sectors.

4 Conclusions

This unnatural experiment conducted in response to COVID-19 has demonstrated the subset of CO_2 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 non-traffic emissions (e.g., industrial sources and residential heating) showed minimal changes in response to the shelter-in-place 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 CO_2 emissions from vehicle traffic are reduced through the electrification of the vehicle fleet, which would also have air quality co-benefits; observing these CO_2 emission changes from such a transition will require sustained measurements as the changes will be more subtle than the abrupt 45% changes seen here.

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