Global to local impacts on atmospheric CO$_2$ caused by COVID-19 lockdown

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Abstract

The world-wide lockdown in response to the COVID-19 pandemic in year 2020 led to economic slowdown and large reduction of fossil fuel CO$_2$ emissions $^{1,2}$, but it is unclear how much it would reduce atmospheric CO$_2$ concentration, the main driver of climate change, and whether it can be observed. We estimated that a 7.9% reduction in emissions for 4 months would result in a 0.25 ppm decrease in the Northern Hemisphere CO$_2$, an increment that is within the capability of current CO$_2$ analyzers, but is a few times smaller than natural CO$_2$ variabilities caused by weather and the biosphere such as El Nino. We used a state-of-the-art atmospheric transport model to simulate CO$_2$, driven by a new daily fossil fuel emissions dataset and hourly biospheric fluxes from a carbon cycle model forced with observed climate variability. Our results show a 0.13 ppm decrease in atmospheric column CO$_2$ anomaly averaged over 50S-50N for the period February-April 2020 relative to a 10-year climatology. A similar decrease was observed by the carbon satellite GOSAT$^3$. Using model sensitivity experiments, we further found that COVID, the biosphere and weather contributed 54%, 23%, and 23% respectively. In May 2020, the CO$_2$ anomaly continued to decrease and was 0.36 ppm below climatology, mostly due to the COVID reduction and a biosphere that turned from a relative carbon source to carbon sink, while weather impact fluctuated. This seemingly small change stands out as the largest sub-annual anomaly in the last 10 years. Measurements at marine boundary layer stations such as Cape Kumukahi, Hawaii exhibit 1-2 ppm anomalies, mostly due to weather and biosphere. At city scale, on-road CO$_2$ enhancement measured in Beijing shows reduction of 20-30 ppm, consistent with drastically reduced traffic during the lockdown, while station data suggest that the expected COVID signal of 5-10 ppm was swamped by weather-driven variability on multi-day time scales. By contrast, a clear stepwise drop of 10-20 ppm at the city-wide lockdown was observed in the city of Chengdu where weather is less variable. The ability of our current carbon monitoring systems in detecting the small and short-lasting COVID signal on the background of fossil fuel CO$_2$ accumulated over the last two centuries is encouraging. The COVID-19 pandemic is an unintended experiment whose impact suggests that to keep atmospheric CO$_2$ at a climate-safe level will require sustained effort of similar magnitude and improved accuracy and expanded spatiotemporal coverage of our monitoring systems.
The unprecedented world-wide lockdown in the first few months of year 2020 led to wide-spread reduced economic activities. As a result, fossil fuel CO$_2$ emissions were reduced by 7.9% in the first 4 months of 2020 due to reduced transportation, industrial and power generation$^2$ and anticipated annual reduction of 4-7%$^1$. This level of emissions reduction is on par with the annual target set out by the Paris climate agreement, but the COVID-19 induced reduction is short-lived as economic activities rebounds subsequently. While the lockdown increased activities such as tele-collaboration that benefit climate, other measures do not lead to transformation needed in energy systems. Monitoring and understanding such processes from global to local scales are of critical importance for achieving our climate goals. Over the last few decades, the scientific community has been developing world-wide carbon monitoring and information systems aiming at enabling the monitoring and verification of emissions reduction goals$^4$-$^7$.

How big is the impact on atmospheric CO$_2$ of this dramatic but short-term reduction in fossil fuel emissions?
A back-of-the-envelope calculation goes as following. Current fossil fuel emissions rate is 10 GtC y$^{-1}$ (Gigatonne carbon per year), of which about half is taken up by carbon sinks on land and in the ocean, with the remaining half left in the atmosphere, resulting in a CO$_2$ increase of 2.5 ppm per year, as observed in a world-wide network of CO$_2$ observatories such as the renowned Mauna Loa station in Hawaii. Assuming 7% reduction or 0.7 GtC for the whole year of 2020 (high estimate of reference$^1$), it would cause a 0.18 ppm relative decrease in global atmospheric CO$_2$ at the end of the year.

In reality, the emissions reduction does not occur uniformly throughout the year, for example, China in February and Europe, US and India in March-April (Fig. S1). The estimated reduction of 7.9% in January-April 2020$^2$ corresponds to a decrease of 0.26 GtC, a rather small quantity for atmospheric CO$_2$. However, we expect the COVID signal to stay largely in the Northern Hemisphere (NH) for these few months because atmosphere inter-hemispheric transport takes approximately one year. We further assume that the carbon sinks have not kicked in because of dormant winter vegetation and sluggish ocean-atmosphere gas exchange. We therefore expect a 0.25 ppm decrease of Northern Hemisphere CO$_2$ at the end of April. This magnitude of change is within the capability of today’s high-accuracy CO$_2$ analyzers, but small for carbon satellites such as NASA’s OCO-2 and the Japanese GOSAT with targeted precision of $\sim$1 ppm and their ground calibration of 0.4 ppm$^3$,$^8$,$^9$.

Challenges also arise from the fact that besides fossil fuel emissions, atmospheric CO$_2$ is also strongly influenced by the changes in the biosphere and atmospheric transport (weather). The growth and decay of the northern vegetation causes a seasonal CO$_2$ amplitude of 6 ppm, while interannual climate variability such as ENSO causes biogenic CO$_2$ changes of 1-3 ppm$^{10-13}$. Thus, a key question is whether a 0.25 ppm COVID signal can be seen among other (natural)
variabilities. We explored this question with carbon cycle models and a suite of space-borne and ground-based observations.

**Modeling atmospheric CO$_2$ response to emissions reduction and biospheric anomalies**

First, we created a high spatial-temporal resolution fossil fuel emissions ($F_{FE}$) dataset with daily emissions data from a near real time product (updated from Liu et al., (2020)$^2$; see Method). The daily country-level data was disaggregated to model grid resolution based on the ODIAC emissions database$^{14}$. As seen in Fig. 1a (detailed temporal evolution in Fig. S1-S2), carbon emissions intensity decreased by more than 5 gC m$^{-2}$ mo$^{-1}$ during February-April 2020 in East Asia, Europe, US and India, relative to the same period in 2019. While consistent with the temporal variations in the original country-level data$^2$, the spatially disaggregated data here further shows emissions reductions concentrated in industrialized regions and areas with high population density such as the North China Plain, India’s Ganges Basin, Northeast and Midwest US, as well as isolated centers such as Sao Paolo.

![Figure 1](image_url)

**Figure 1.** Anomalies for the period of February-April 2020 of (a) Fossil fuel emissions ($F_{FE}$); (b) terrestrial biosphere-atmosphere flux ($F_{TA}$); (c) atmosphere transport model simulated column CO$_2$ (vertically averaged); (d) Observed column CO$_2$ from GOSAT. Anomalies in (a) are relative to 2019 while those in (b)-(d) are relative to climatology of 2010-2019. Fluxes are in gC m$^{-2}$ mo$^{-1}$, and CO$_2$ in ppm. Locations in (c) are selected ground CO$_2$ observation stations for model-data comparison.
For terrestrial biosphere-atmosphere flux ($F_{TA}$), we used a dynamic vegetation and terrestrial carbon cycle model VEGAS $^{10,15}$, while ocean-atmospheric flux came from a multi-model product (see Method). The biospheric fluxes (Fig. 1b) have regional variations often larger than $F_{FE}$ reduction, driven by climate variability. Overall, the terrestrial biosphere had wide-spread negative anomalies that was particularly strong in April (Fig. S3). As a result, the spatial pattern of net flux $F_{net}$ was dominated by biospheric fluxes.

Interestingly, when summed up globally, the magnitude of 2020 $F_{FE}$ anomaly relative to 10-year climatology is comparable to that of $F_{TA}$ (Fig. 2a), each about 50 MtC mo$^{-1}$ decrease by April 2020. This is because fossil fuel emissions are reduced almost everywhere during COVID-19 lockdown, whereas the positive and negative anomalies in $F_{TA}$ tend to cancel out.

Consequently, the total flux anomaly $F_{net}$ reaches -100 MtC mo$^{-1}$.

These fluxes were then used to drive the community GEO-Chem atmospheric transport model for the period of January 2008-May 2020 (see Method). The output of the model is a 4-dimensional depiction of spatial-temporal evolution of atmospheric CO$_2$ that can be compared to various types of CO$_2$ observations, as well as expected COVID impact (Fig. S4-S7). Using a method termed DCA (Detrended Climatology and Anomaly; see Method), in which a CO$_2$ time series is detrended to remove the low-frequency signal and climatological seasonal cycle, we calculated sub-annual anomalies of column CO$_2$, shown in Fig. 2b. After a large positive anomaly in Jan 2020, the CO$_2$ anomaly trended downward, and was 0.19 ppm lower than long-term climatology in March-April 2020, and 0.36 ppm lower in May (Fig. 2b shaded period). This anomaly is twice the second lowest monthly value in July 2016 and stands out among the past 10 years, and particularly so for the same season.

**Observations from carbon satellite**

The Japanese GOSAT carbon satellite, launched in 2009, has collected column CO$_2$ (XCO$_2$) data for over 10 years. The spatial pattern of February-April 2020 GOSAT anomalies (Fig. 1d) are similar to the model over India, southern Africa, South America and central US where large

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**Figure 2.** (a) Anomalies of global total Fossil Fuel Emissions ($F_{FE}$), terrestrial biosphere-atmosphere flux ($F_{TA}$), and net fluxes ($F_{net}$) relative to a 10 year climatology; (b) Detrended anomalies of model simulated column CO$_2$ with closed black circles marking each year’s February, March and April, while red line is the same but for GOSAT satellite column CO$_2$ data, both averaged for land area between 50S-50N to make them as comparable as possible. Vertical shading of February-May 2020 indicates the ‘COVID-19 period’.
negative values are wide-spread, though the overall spatial correlation is modest and significant sign differences exist near the northern edge in Eurasia (Fig. 1 c and d). Detailed monthly evolution shows similar broad patterns of agreement as well as larger detailed differences (Fig. S8 vs. S9). In a sense, the differences are expected because of satellite’s sparse spatial-temporal sampling, particularly at higher latitudes and cloudy regions. However, the signal-to-noise ratio is enhanced via spatial-temporal averaging: the time series of CO₂ anomalies averaged over 50S-50N (Fig. 2b) shows reasonable agreement. Most encouragingly, the drop in 2020 stands out both in model and GOSAT.

To better appreciate how unusual year 2020 was, we plotted the CO₂ seasonal cycle from May 2019 to April 2020 against those of the previous 10 years (Fig. 3). The 50S-50N land average CO₂ for especially March-April is outside the standard deviation as well as the envelope of the previous 10 individual years for both model and GOSAT. Such agreement lends confidence in using both model and satellite column CO₂ for short-term anomaly detection. We also analyzed data at smaller scales including the NH 0-50N where strongest COVID-signal is expected. The model shows clear negative anomaly but the corresponding GOSAT signal is not as statistically significant as in 50S-50N (Fig. S10), likely due to increase in noise towards smaller scales. The more robust 50S-50N signal has contribution from GOSAT’s ability to capture the anomalies in the Southern Hemisphere which is largely a biospheric signal. Similarly, a large decrease in GOSAT anomaly for Eastern China in February 2020 (Fig. S11), though may be partly related to COVID reduction, is not statistically robust.
We conducted two additional model sensitivity experiments to delineate the effects of biosphere, atmospheric transport (weather), and COVID reduction in $F_{FE}$ (See Method and aspects of the detailed result in Fig. S4-S7). The monthly evolution of CO$_2$ anomalies from these experiments (Fig. 4) indicate that the roles of the biosphere, weather, and COVID vary from month to month. In February 2020, biosphere has a near zero but positive anomaly, while COVID effect steadily increases from February to May. The weather effect was large in March and May to drawdown CO$_2$, but small in both February and April, all in comparison with 2019 by model design. Averaged over February-April, the biosphere contributed 0.030, weather 0.029, and COVID 0.069 ppm, leading to a February-April average of 0.128 ppm CO$_2$ drawdown with March and April both about 0.18 ppm. By percentage, the biosphere, weather, and COVID contributed 23%, 23%, and 54%, respectively. In May 2020, all three factors contributed to CO$_2$ drawdown, leading to a rapid decrease to 0.36 ppm.

In summary, the three factors impacted CO$_2$ in an intricate way. In the period February-May 2020, the biosphere was recovering from a large carbon loss (relative to climatology) from year 2019, mostly in South America, Africa, and Australia in response to a moderate El Nino$^{10}$, with additional CO$_2$ uptake from Northern Hemisphere including South Asia and Siberia (Fig. S3). COVID emissions reduction was the most spatiotemporally consistent factor, contributing to majority of the CO$_2$ decrease. The weather impact on CO$_2$ fluctuated from month to month. The weather effect is not predominant because its variability tends to be averaged out on global scales. Its importance rises at smaller scales to which we turn our attention now.

**CO$_2$ changes at surface atmosphere background stations**

Similar to the global-scale analysis above, we also analyzed data from atmospheric background CO$_2$ stations from the NOAA global reference network ObsPack$^{16}$ (see Method). Fig. 5 compares model with surface observation at five marine boundary layer stations that span the
remote Pacific region from North to South. Flask sampling at these sites is carefully conducted to represent atmospheric background concentrations on the scale of hundreds to thousands of kilometers. Among these stations is Cape Kumukahi, Hawaii (KUM), a site downslope of the Mauna Loa observatory, but is better than Mauna Loa at capturing large-scale atmosphere background signal and more comparable with model which does not resolve the island.

The anomalies at Kumukahi are relatively small in February and March, 2020, but decrease rapidly to lower than -1 ppm in April. Model and observation are broadly similar, in particular, the decrease in April. It is tempting to associate this drop with COVID reduction. However, a closer look at model sensitivity experiments (Fig. S12) reveals large month-to-month fluctuations from biosphere and weather, for example, a positive anomaly up to +1 ppm from the biosphere and a similarly large negative anomaly from weather in March. Of the total CO₂ drop of 1 ppm in April, 0.5 comes from biosphere, 0.5 from weather, and only 0.2 ppm from COVID.

Unlike a decrease in Hawaii, CO₂ at Barrow, Alaska (BRW) shows an increase in early 2020, while Midway Island in the North Pacific Ocean (MID) has a decrease in February-March and rebound in April, both attributable to the biosphere and/or weather (Fig. S12). Thus, while the sub-annual signal of 1-2 ppm at these marine surface stations is a few times larger than global mean column anomalies seen by the satellite, the variability at a given station is dominated by the biosphere and weather. Nevertheless, the 0.1~0.2 ppm decrease due to COVID-19, though
smaller than biospheric and weather effect, are separable using model, and is consistent with the global-scale COVID induced drop discussed above. The overall consistency between model and station observations suggests the ability of both model and observation in capturing these sub-annual changes, regardless of the origin, thus lending support for interpreting the signal using model experiments.

**City-scale CO₂ changes**

Because major fraction of emissions comes from cities with high human activities, one can expect large COVID signal in urban CO₂ data. Thus, we analyzed CO₂ measurements in Beijing and Chengdu.

Surface observations in Beijing shows CO₂ for the winter-spring (December 2019-April 2020) compared to the same period the year before (Fig. 6a). During the pre-COVID period of December-January, CO₂ is significantly higher in 2020 than the year before, because this winter’s atmosphere was less ‘ventilated’. February was dominated by two high-CO₂ weather events, one in each year. The expected low CO₂ values due to COVID in January-February (Fig. 6b) ‘predicted’ by the model do not have a clear correspondence in the weather-dominated CO₂ fluctuations, and in general, the modeled magnitude of change is much smaller than the variability. During March-April, the difference between the two years decreases to much smaller values. It is tempting to explain this difference as the result of emissions reduction, but it is mostly brought about by weather regime shift in the spring season with dominantly northwesterly wind from Mongolian Plateau. Thus, although COVID-19 signal is large, it is ‘buried’ in even larger weather noise. Other cities are similarly dominated by weather (Fig. S13), for example, a monthly drop of 1-2 ppm at New York City and Delhi, an increase of 1-2 ppm in Washington DC and Paris.

Interestingly, CO₂ measured at the city of Chengdu shows a stepwise drop on January 24, the day before traditional Chinese Lunar New Year, followed by city-wide lockdown with little urban activity for the next 1-2 months (Fig. 7). The difference between the month before and after the lockdown is 20-30 ppm and the temporal characteristics is consistent with a COVID signal. Concurrent particulate matter (PM2.5) measurements support this interpretation because the
short-lived PM2.5 has similar pattern on timescales shorter than a few days, but it has much less monthly and longer timescale variations compared to CO₂.

Why is the COVID signal relatively clear in Chengdu, but not in Beijing? The answer lies in the differences in weather. Chengdu, situated within the Sichuan Basin in southwestern China, is surrounded by great mountain ranges including the Tibetan Plateau and has generally very calm weather with a famously known atmospheric inversion layer that is rarely broken¹⁷, whereas Beijing, being at the edge of the North China Plain is subject to large weather fluctuations, frontal passages and seasonal shifts. Thus, while weather tends to dominate in Beijing, its variation is sufficiently small in Chengdu to allow COVID signal to be revealed.

**Figure 7.** Hourly CO₂ and PM2.5 measured in Chengdu, a city in the Sichuan Basin to the east of Tibet plateau. An abrupt drop on Jan 24, 2020, following the Lunar New Year and city-wide lockdown is clearly visible.

**Direct observation of on-road CO₂ concentration** has been conducted in Beijing periodically since 2017 using mobile platforms¹⁸,¹⁹ (See Method). Some of these ‘CO₂-tracking’ trips took advantage of light-weight low-cost CO₂ sensors²⁰. Three trips were selected from before, during, and after the COVID-19 lockdown while minimizing differences in other factors such as weather condition, rush hour, and weekend effects. The average CO₂ is 513 ppm before, 455 ppm during, and 501 after the height of lockdown (Fig. 8). To further remove the compounding effect of still somewhat differing weather conditions, we subtracted CO₂ concentration measured at the IAP tower station. This difference can be thought as a traffic-induced on-road ‘CO₂ enhancement’ relative to a ‘city background’. This ‘traffic enhancement’ is 65, 30 and 50 ppm respectively for the three periods. The more than 30 ppm less traffic CO₂ during COVID, and still somewhat depressed value during recovery is consistent with direct traffic data, not surprisingly, because
the reduced transportation is the largest source of CO\textsubscript{2} reduction during lockdown in cities.

![Figure 8. On-road CO\textsubscript{2} concentration measured before, during and after COVID-19 lockdown in Beijing. These ‘CO\textsubscript{2} tracking’ car trips covered the city’s 4 major transportation arteries, from the Second (innermost) to the Fifth Ring Road. The west-east distance of the Fifth Ring Road is about 30 km. Each dot is 1-minute average of the original 1s or 2s data. Station data from the IAP tower, marked by black triangle, is used as ‘city background’ to compute on-road enhancement in the text.](image)

**Discussion**

The detectability of COVID-19 CO\textsubscript{2} signal depends strongly on spatial and temporal scales. Our results show that the carbon satellite GOSAT is able to detect a short-term global mean CO\textsubscript{2} anomaly decrease of 0.2-0.3 ppm, a number below the satellite instrument’s targeted accuracy of individual measurements. This somewhat surprising result is made possible by spatial and temporal averaging to compensate for the sampling sparsity, and importantly also by the cancellation of biosphere and weather variability at large-scale. As a result, the drop in global-scale CO\textsubscript{2} anomalies was dominated by the spatially coherent COVID emissions reduction, followed by a biospheric recovery from previous year’s relative carbon loss, which became more important in the spring season, while weather impact fluctuated. One implication for detection is the need for meticulous approaches in enhancing signal-to-noise ratio and maximizing spatial-temporal data coverage\textsuperscript{21,22}. A critical perspective here is the focus on sub-annual time scale which has received little attention in the past compared to the much larger CO\textsubscript{2} seasonal cycle and interannual variability. Our results suggest that current observation and modeling capabilities can depict sub-annual variations with some consistency, and the COVID period has the largest sub-annual CO\textsubscript{2} anomaly in the last 10 years.

Surface observations of the atmospheric background CO\textsubscript{2} concentration have variabilities up to 1-2 ppm, substantially larger than the ~0.2 ppm COVID fossil signal. However, the modeling results are sufficiently realistic in capturing sub-annual variabilities consistent with station observations, lending support in using model experiments to separate the COVID effect from the larger weather and biospheric variability.
At urban scale in many cities such as Beijing, New York City and Paris, atmospheric variability dominates the signal. Seasonal variations in weather patterns prevented us from discerning the COVID signal with confidence despite of the large fossil fuel emissions changes expected there. A major caveat is that the model resolution is too coarse to resolve the cities properly and the real signal is likely stronger than seen here and it would be better simulated by meso-scale models. Moreover, where weather variability is modest such as in Chengdu, the lockdown caused a clear CO₂ reduction. Additionally, decrease in on-road CO₂ enhancement larger than 20 ppm in Beijing was observed which is perhaps the most direct observation of localized emissions reduction.

Despite of the dramatic reduction in economic activities during 2020 COVID-19 worldwide lockdown, the short-duration of the event has left only a small signature in the atmospheric CO₂ which results from fossil fuel emissions accumulated over two hundred years due to CO₂’s long life-time in the atmosphere. Nevertheless, our analysis demonstrates that its global-to-local impacts are already detectable, albeit still imprecisely, by current carbon monitoring systems using a variety of approaches, and that meaningful causality attribution to fossil fuel, biosphere and weather can be made by combining model and observations. Continued improvement and expansion of such capabilities can play a critical role in monitoring and verification of fossil fuel emissions reduction target at local, country, and global scales. They can also facilitate climate mitigation efforts from governments, cities, institutions and citizens.

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Author contribution
NZ, PH, DL and RD designed the study. NZ and ZQL designed and ZQL conducted the model simulations. CM, DL, RD, and ZQL did the model development. QC conducted the biosphere model simulations. ZL, TO, ZQL, NZ, PH produced the fossil fuel emissions data. TO and SM provided GOSAT interpretation. PH, BY, PW, WS, NZ, and DL organized the observations and CO₂-Tracking trips in Beijing. NZ, ZQL and DL led the analysis and wrote the paper, and all participated in synthesis and helped writing.

Competing interests
The authors declare no competing interests.
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Method

Atmospheric transport model simulation

To simulate the atmospheric CO$_2$, the model solves the carbon mass balance equation:

$$\frac{dCO_2}{dt} = F_{net} \equiv F_{FE} + F_{TA} + F_{OA} \quad (1)$$

where $\frac{dCO_2}{dt}$ is the atmospheric CO$_2$ growth rate, $F_{FE}$ is fossil fuel emissions, $F_{TA}$ is terrestrial to atmosphere flux, $F_{OA}$ is ocean to atmosphere flux, and $F_{net}$ is net surface to atmosphere flux. The model is run in a ‘forward’ fashion for each 3-dimensional model grid point (location), forced by the three fluxes, as well as meteorological variables for atmospheric transport and mixing. Here we use GEOS-Chem atmosphere transport model v12.5.0 (http://acmg.seas.harvard.edu/geos/) at a horizontal resolution of 4°×5° with 47 vertical levels. The fluxes (below) at different resolutions are re-gridded to 4°×5°. The model is driven by the meteorology field MERRA2 from the NASA Global Modeling and Assimilation Office. Details of setup and evaluation were described earlier$^{23,24}$. The simulation period was from 1 January 2008 to 31 May 2020, and data after January 2010 were used for analysis.

Fossil fuel CO$_2$ emissions

$F_{FE}$ combines a number of sources, including the Global Carbon Project (GCP) annual country-level carbon budget for 1959-2018$^{25}$ with update for 2019 by Le Quere et al. (2020)$^1$, daily data for 2019-2020 from Liu et al. (2020)$^2$, the TIMES hourly scaling factor of Nassar et al. (2013)$^{26}$, and the spatial information of the ODIAC database of Oda et al. (2018)$^{14}$.

Recently, a daily resolution, country-level data became available$^2$. This novel dataset achieved daily resolution by taking advantage of a variety of sector-based energy and economic activity statistics, including real-time traffic data and daily electricity generation data of major power suppliers. However, the Liu et al. (2020) data was available only for early 2019 and 2020, and for this work, it was updated to cover the period of Jan 2019 through May 2020. For the years 2008-2018 when we do not have daily resolution data, we use the 2019’s daily variation as a surrogate but retain their annual total. Because the emissions of Liu et al. (2020) for 2019-2020 are slightly different from GCP, in order to maintain the consistency of $F_{FE}$ from 2018 to 2019-2020, we use the country-level GCP fossil fuel values as a constrain to rescale the yearly total $F_{FE}$ from 2008 to 2020, and the same scaling factor for 2019 is used for 2020 to obtain a harmonized time series. Further, we combine the diurnal scaling factor from the TIMES method of Nassar et al.$^{26}$ and the daily national CO$_2$ emissions of 2019 of Liu et al.$^2$ to obtain an hourly country-level CO$_2$ emission in 2019 and 2020.

The gridded spatial information comes from the Open source Data Inventory of Anthropogenic CO2 emission (ODIAC)$^{14}$. ODIAC uses the annual country-level fuel consumption bases CO$_2$ emissions estimates$^{27}$ and disaggregate to 1 km or 1 degree resolution using satellite night light
observations and point source data. The annual data was disaggregated to monthly based on a
climatological seasonal cycle. Here we simply disaggregated the country-level hourly data above
to $1^\circ \times 1^\circ$ with the spatial information of ODIAC. Since COVID-19 reduction is more
concentrated in cities with major reduction in transportation\textsuperscript{2,28}, this disaggregation in proportion
to ODIAC’s spatial pattern may underestimate the reduction in metropolitan regions.

Altogether, the method can be summarized in the following equation for 2008~2018:

$$F_{FE}^{c,i,y,th} = ODIAC_{tot}^{c,i,y} \times \frac{GCP_{tot}^{c,y}}{ODIAC_{tot}^{c,y}} \times \frac{LZ^{c,2019,td}}{LZ_{tot}^{c,2019}} \times TIMES^{i,j,tdiurnal}$$

and for 2019~2020:

$$F_{FE}^{c,i,y,th} = ODIAC_{tot}^{c,i,y,2018} \times \frac{GCP_{tot}^{c,2019}}{ODIAC_{tot}^{c,2018}} \times \frac{LZ^{c,y,td}}{LZ_{tot}^{c,2019}} \times TIMES^{i,j,tdiurnal}$$

where $y$ is year, $th$ is hour, $td$ is day, $tdiurnal$ is the diurnal cycle. $c$ is country, $i$ is longitude, $j$ is
latitude, tot is the yearly total value. $F_{FE}^{c,i,y,th}$ is the emission of country $c$ at location $i$, $j$ at time $th$
of the year $i$. The four datasets used to obtain this harmonized labeled ODIAC, GCP, TIMES and
LZ, with LZ for our updated Liu et al. (2020) dataset.

The terrestrial biospheric flux

$F_{TA}$ is simulated by a dynamic vegetation and terrestrial carbon cycle model VEGAS\textsuperscript{10,15}. The
model is forced by observed climate variables including monthly precipitation, hourly
temperature and radiation, and historical land use pattern as well as atmospheric CO$_2$. The model
was run at hourly time step and $0.5^\circ \times 0.5^\circ$ resolution from 1901 to Apr 2020. This version 2.6 of
VEGAS follows largely the simulation protocol of the TRENDY\textsuperscript{29} and the MsTMIP\textsuperscript{30} terrestrial
model intercomparison projects with some model and near real time (NRT) forcing data updates.
Carbon cycle models have been applied to long-term, interannual and seasonal variations
extensively, but rarely in sub-annual changes of interest here. VEGAS has been shown to be
among the models better at simulating such short-term changes\textsuperscript{31,32}.

The ocean-atmosphere carbon flux

$F_{OA}$ uses the spatial pattern of pCO$_2$ observation derived fluxes of Takahashi et al. (2009)\textsuperscript{33}. To
obtain the temporal variation, we rescaled the Takahashi spatial pattern for the year 2013 with
the temporal evolution of $F_{OA}$ from the GCP annual carbon budget analysis which is based on
estimates from multiple ocean carbon cycle models\textsuperscript{25}. The carbon budget was up to only 2018.
For the year of 2019 and 2020, the GCP ocean values are linearly extrapolated using the values
from the previous 10 years. The annual carbon budget thus does not contain possible sub-annual
contribution from ocean, which is generally believed to be small compared to land and fossil flux
anomalies.

Model sensitivity experiments
To delineate contribution to CO$_2$ changes from fossil fuel emissions $F_{FE}$, biospheric flux $F_{TA}$, and weather, we designed three sets of experiments:

1. BWC (Biosphere+Weather+COVID): the full experiment described above with realistically varying biospheric fluxes $F_{TA}$, weather, and $F_{FE}$ including COVID-induced emissions reduction.

2. BW (Biosphere+Weather, no COVID): as in BWC, but replace $F_{FE}$ of 2020 with that of 2019.

3. B (Biosphere only): as in BW, but replace all years’ meteorology (wind, etc.) with that of 2019.

Thus, compared to BWC, Experiment BW removes the effect of COVID emissions, while Experiment B further removes weather effect. The differences among these experiments show the effect on CO$_2$ of each individual factor. In Fig. 4, anomaly for experiment B is calculated as detrended anomaly, while those of BW and BWC represent the differences between 2020 and 2019, following the experiment design.

**CO$_2$ observations: satellite column CO$_2$ from GOSAT**

The satellite column CO$_2$ data is Level-3 product from the National Institute for Environmental Studies (NIES) [22](http://www.gosat.nies.go.jp/en/about_5_products.html). The L3 data derived from the L2 data with spatial interpolation using Kriging technique. The data is at 2.5°×2.5° resolution, available from August 2009 to April 2020. There are 3 months of missing data (December 2014, January 2015 and December 2018), which were gap-filled with spline method. There are known biases in oceanic glint data, so we only used land data in our analysis. For this reason, regional average analyses in such as Fig. 2b are over land only for both model and GOSAT to facilitate comparison. Additional uncertainty comes from missing GOSAT data in regions such as the core of the Amazon due to persistent cloud cover and the northern boundaries where large solar zenith angle may lead to larger uncertainty (e.g., Fig. 15 of reference [22]).

**Global network of surface CO$_2$ observations**

The surface station data are from the ObsPack framework [16] that collects a great variety and numbers of in-situ, flask sampling, aircraft and other CO$_2$ measurements. The five stations data used in our analysis are all flask sampling data. These are baseline stations managed by NOAA that have been in operation for several decades. Great care is taken to sample air representative of large-scale atmospheric background condition. Data product used here is GLOBALVIEW+5.0, with most recent update ObsPack NRT V5.0 provided by NOAA’s CarbonTracker team [34,35]. The most recent year’s data have been quality-controlled by an automated procedure, and they may still be subject to modifications from further manual quality control.

**City CO$_2$ station observations**

A network of 6 tower stations using high accuracy Picarro CO$_2$ analyzers has been running since 2018 as part of the Beijing-Tianjin-Hebei (JJJ) carbon monitoring project [19], run by the Chinese Meteorological Administration (CMA) and the Institute of Atmospheric Physics (IAP) of the
Chinese Academy of Sciences. The CO₂ analyzers are calibrated 4 times a day, with calibration gas tracing to World Meteorological Organization (WMO) standard. The data have a nominal accuracy of 0.1 ppm. A network of low-cost CO₂ sensors has been running in various stages of development since 2016, as a collaborative effort between IAP, the University of Maryland, and the US National Institute for Standards and Technology (NIST). These sensors were found to be able to achieve an accuracy of ~5 ppm after calibration and environmental correction. The data used in this paper for Beijing stations are measured with Picarros while the data in Chengdu was from a low-cost sensor node with 3 individual CO₂ sensors.

**On-road CO₂ observation in Beijing before, during and after COVID-19 lockdown**

We conducted several on-road CO₂ measurements in Beijing and surrounding area using mobile platforms before, during and after COVID-19 lockdown. Because urban CO₂ concentration is strongly influenced by weather, we selected three trips with closest weather as possible for the days of February 20 of 2019, February 21 of 2020, May 9 of 2020. Additionally, we calculate the on-road CO₂ enhancement relative to a city ‘background’ measured at the IAP tower station. We used CO₂ sensors of different accuracy including Picarro and LI-COR LI-7810, both mounted inside car with air inlet from above roof. We also used low-cost sensors mounted on windshield, calibrated before and after each trip. Some of the sensors were in the same car with Picarro and their agreement was found to be within 5 ppm.

**Analysis of CO₂: separate sub-annual anomalies from trend and seasonal cycle**

Atmospheric CO₂ data contains variability on a variety of time scales, from long-term increasing trend driven by fossil fuel emissions and carbon sinks, Decadal variations, interannual variability dominated by ENSO, to a prominent seasonal cycle in response to the annual growth and decay of the biosphere. The possible COVID-19 signal of interest here lasts for few months on sub-annual (month to intra-seasonal) timescales. Monthly-scale high-frequency variabilities are generally less well studied and are often filtered out so as to focus on seasonal and longer-term changes.

Here we calculate sub-annual anomalies using a 4-step ‘detrended anomaly’ approach termed DCA (Detrending, Climatology, Anomaly):

1) A 12-month running mean is applied to the original CO₂ data. The running mean contains mostly signals longer than a year, including long-term trend, interannual to decadal variations (Fig. 9a)

2) This running mean is then subtracted from the original CO₂ data. The result is considered ‘detrended’ and is dominated by seasonal cycle (Fig. 9b black line)

3) A climatology is then calculated as the mean seasonal cycle (Fig. 9b green line).

4) The sub-annual anomalies (detrended anomalies) is the difference between the detrended CO₂ and its climatology
The approach using running mean to remove low-frequency signals has been used by various authors, e.g., to study the CO$_2$ seasonal amplitude change. The last two steps consist of a standard definition of climatology and anomaly. In comparison to the DCA method, the standard climatology/anomaly method (simply called CA method here) does not involve detrending, and it retains low-frequency signal. Therefore, the DCA method is suitable for finding CO$_2$ sub-annual anomalies, while the CA method is used for flux analysis such as in Fig. 2a which contains both interannual and sub-seasonal information.

**References for Method**

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