Short-term reduction of regional enhancement of atmospheric CO\(_2\) in China during the first COVID-19 pandemic period

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Abstract

Recent studies have reported a 9% decrease in global carbon emissions during the COVID-19 lockdown period; however, its impact on the variation of atmospheric CO\(_2\) level remains under question. Using atmospheric CO\(_2\) observed at Anmyeondo station (AMY) in South Korea, downstream of China, this study examines whether the decrease in China’s emissions due to COVID-19 can be detected from the enhancement of CO\(_2\) mole fraction (\(\Delta\)CO\(_2\)) relative to the background value. The Weather Research and Forecasting–Stochastic Time-Inverted Lagrangian Transport model was applied to determine when the observed mole fractions at AMY were affected by air parcels from China. Atmospheric observations at AMY showed up to a −20% (−1.92 ppm) decrease in \(\Delta\)CO\(_2\) between February and March 2020 compared to the same period in 2018 and 2019, particularly with a −34% (−3.61 ppm) decrease in March. \(\Delta\)CO, which was analyzed to explore the short-term effect of emission reductions, had a decrease of −43% (−80.66 ppb) during the lockdown in China. Particularly in East China, where emissions are more concentrated than in Northeast China, \(\Delta\)CO\(_2\) and \(\Delta\)CO decreased by −44% and −65%, respectively. The \(\Delta\)CO/\(\Delta\)CO\(_2\) ratio (24.8 ppb ppm\(^{-1}\)), which is the indicator of emission characteristics, did not show a significant difference before and after the COVID-19 lockdown period (\(\alpha = 0.05\)), suggesting that this decrease in \(\Delta\)CO\(_2\) and \(\Delta\)CO was associated with emission reductions rather than changes in emission sources or combustion efficiency in China. Reduced carbon emissions due to limited human activity resulted in a decrease in the short-term regional enhancement to the observed atmospheric CO\(_2\).

1. Introduction

To prevent the rapid spread of the novel coronavirus disease, COVID-19, Wuhan City imposed a lockdown on 23 January 2020, and preventive measures, such as confinement, school and workplace closures, physical distancing, and social restrictions were implemented throughout China from late January to April 2020. These measures dramatically reduced economic and social activities, and consequently, the emission of carbon dioxide (CO\(_2\)) (Lauri Le Quéré et al 2020, Liu et al 2020, Myllyvirta 2020). A recent study by Le Quéré et al (2020) estimated a −2.6% (−242 Mt CO\(_2\)) change in CO\(_2\) emission in China from 1 January to 30 April 2020, compared to that in 2019. Similarly, Liu et al (2020) discovered a 3.7% reduction (−187.2 Mt CO\(_2\)) in China from 1 January to 30 June 2020, with 18.4% and 9.2% reductions in February...
and March 2020, respectively, compared to the same period in 2019. Therefore, it is crucial to determine whether the influence of emission reductions in China is strong enough to be detected from atmospheric CO\textsubscript{2} observations because atmospheric CO\textsubscript{2} levels have a direct impact on climate change.

Although the recent lockdown in China, and the resulting decrease in emissions, have caused a reduction in concentrations of air pollutants measured by ground and satellite observations in East Asia (Forster et al 2020, Le et al 2020, NASA 2020, Shi and Brasseur 2020, Wang et al 2020a), the atmospheric CO\textsubscript{2} levels across various locations in East Asia reached their highest levels in 2020 (figure 1): e.g. Anmyeondo (AMY) in South Korea, Minamitorishima (MMN) in Japan, and Mt Waliguan (WLG) in China. It was expected that the dramatic decrease of local emission across East Asia would reduce the atmospheric CO\textsubscript{2} measured at local stations; however, such a phenomenon was not observed due to the challenging nature of signal detection for CO\textsubscript{2} observation. First, CO\textsubscript{2} is a long-lived gas; thus, even if emissions are reduced for a few weeks, the background levels remain unchanged (Friedlingstein et al 2020). Second, the signal of reduced CO\textsubscript{2} emissions is small compared to the monthly CO\textsubscript{2} uptake and release by terrestrial ecosystems (Peters et al 2017, Le Quéré et al 2020).

Third, atmospheric transport is rapid in the Northern Hemisphere and quickly mixes the emission signal with terrestrial and oceanic fluxes on time scales of a few days to weeks, where strong synoptic CO\textsubscript{2} variations are driven by meteorological conditions (Ballantyne et al 2012, Peters et al 2017, Le Quéré et al 2020). To overcome these challenges, it is necessary to isolate the recent change in CO\textsubscript{2} mole fractions above the background level, to exclude the influence of the terrestrial ecosystem, and to minimize the mixing effect of atmospheric transport.

This study investigates whether the emission decrease in China due to COVID-19 was detected in the CO\textsubscript{2} and CO levels measured at the AMY global atmosphere watch (GAW) station, located on the west coast of South Korea, downwind of China. In addition to the regional fluxes of South Korea, these measurements are affected by Northeast Asian fluxes, including those in China (Yun et al 2020). Although lockdown in China lasted until April 2020, we focused the period from February to March 2020, when the impact of the terrestrial ecosystem might be neglected due to vegetation dormancy (Piao et al 2006) and CO\textsubscript{2} emissions in China decreased dramatically by 14% (Liu et al 2020). Our data were divided into two time periods: (a) the LOCK period (lockdown period in China, February to March 2020), and (b) the REF period (reference period, February to March 2018 and 2019). Data obtained during the LOCK period were compared with those obtained during the REF period. Because the CO\textsubscript{2} and CO levels measured at AMY are affected by a mixture of carbon emissions from several regions owing to atmospheric transport, we used the Weather Research and Forecasting–Stochastic Time-Inverted Lagrangian Transport (WRF-STILT) model to classify the air parcels from China.

2. Methods

2.1. \(\Delta\text{CO}_2\) and \(\Delta\text{CO}\) levels at AMY

The AMY station (36° 32′ 19″ N, 126° 19′ 48″ E, and 47 m asl), as a regional station under the GAW programme of the World Meteorological Organization, monitors atmospheric greenhouse gases and air pollutants in South Korea (figure 1(a)). The station is operated by the Korea Meteorological Administration/National Institute of Meteorological Sciences. It has continuously recorded CO\textsubscript{2} and CO levels since 1999 and 2004, respectively (Zellweger et al 2019). A cavity ring-down spectroscopy analyzer (model G2301, Picarro, CA, USA) continuously monitors atmospheric CO\textsubscript{2}; the measurement uncertainty is within 0.116 ppm in the 68% confidence interval (Lee et al 2019). The CO analyzer (model 48i, Thermo Fisher, MA, USA), based on non-dispersive infrared (NDIR) technology, has an uncertainty within ±29.076 ppb in the 68% confidence interval (Zellweger et al 2019).

Because CO\textsubscript{2} and CO remain in the atmosphere for at least 300 years and 2 months, respectively (Khalil and Rasmussen 1990, Buis 2019), the measured CO\textsubscript{2} and CO mole fractions can be attributed to two factors: the recent enhancement and long-maintained background level. To capture the increase above the background level, i.e. enhancement from recent anthropogenic emissions, it is necessary to remove background levels for CO\textsubscript{2} and CO. The MNM station (24° 17′ 18″ N, 153° 58′ 60″ E, and 7.1 m asl) was chosen as the background atmospheric station to obtain the enhancements in CO\textsubscript{2} (\(\Delta\text{CO}_2\)) and CO (\(\Delta\text{CO}\)) above the background. An NDIR analyzer (model LI-7000, LI-COR Biosciences, Inc., NE, USA) and gas chromatography (reduction gas detector) analyzer (TRA-1, Round Science Inc., Kyoto, Japan) were used to monitor the CO\textsubscript{2} and CO levels at MNM, respectively. In addition, we applied the WLG flask data (Dlugokencky et al 2020, Petron et al 2020) to calculate \(\Delta\text{CO}_2\) and \(\Delta\text{CO}\), and there were no significant differences in the main findings (see supplementary note 1 available online at stacks.iop.org/ERL/17/024036/mmedia WLG background station). The WLG station was not used as the main background station in this study, as it provides flask-sampled data and the amount of data during the analysis period is small. The choice of background did not lead to significant changes in our...
Figure 1. The spatiotemporal characteristics of CO\textsubscript{2} in East Asia. (a) Map of fossil fuel CO\textsubscript{2} emissions from Open-source Data Inventory for Anthropogenic CO\textsubscript{2} in February 2019 (Oda and Maksyutov 2011) and locations of WLG, AMY, and MNM stations. (b) Time series of CO\textsubscript{2} levels measured at AMY, MNM, and WLG from 2017 to 2020. Data that were regarded as background data were used for MNM and WLG. Lines for AMY and MNM indicate daily-averaged data from hourly data and thick line for AMY indicates weekly-averaged data. Dots for WLG indicate day-to-day sparsely sampled flask data. Orange and gray shaded regions indicate REF (February to March 2018 and 2019) and LOCK periods (February to March 2020), respectively.

2.2. WRF-STILT experiments

WRF model version 3.9.1 (Skamarock and Klemp 2008) was used to generate meteorological fields to drive the STILT model (Lin et al. 2003); the grid spacing was 27 km (103° E–138° E and 20° N–51° N) (see supplementary note 2 WRF configuration). Reanalysis data from the Global Forecast System produced by the National Centers for Environmental Prediction were applied as boundary conditions to the WRF model at a horizontal resolution of 0.5° every 6 h.

The STILT model, driven by meteorological fields simulated by the WRF model, was utilized to determine when the observed mole fractions at AMY were affected by China. WRF-STILT is an effective tool for simulating realistic atmospheric transport using the Lagrangian particle dispersion model within the planetary boundary layer (Nehrkorn et al. 2010). It releases backward 3D air parcel trajectories with stochastically turbulent dispersion from the observation location (receptor) to a potential source region that affects the receptor and counts the scattered air parcels (footprints) in each grid. As defined in equations (7) and (8) by Lin et al.
Figure 2. The workflow of the data processing of CO$_2$ and CO observations measured by AMY, MNM, and WLG to calculate enhancements values with applying the non-stagnant conditions.
hourly $\Delta CO_2$ (or $\Delta CO$) on the same day into daily data to remove the autocorrelation (Ebisuzaki 1997, Wang et al 2013). Averaging hourly $\Delta CO_2$ and $\Delta CO$ data to daily data resulted that each data had no autocorrelation. Also, we used 95% confidence intervals to express plausible ranges for the sample means, and all ranges reported via $\pm$ are the 95% confidence intervals of the mean.
3. Results

3.1. Changes in ΔCO₂ and ΔCO during lockdown period

The atmospheric CO₂ levels measured at AMY, MNM, and WLG show seasonal variability and continue to increase over time (figure 1(b)). The CO₂ growth rates from 2017 to 2020 were 2.94, 1.92, and 1.82 ppm year⁻¹ at AMY, MNM, and WLG, respectively. Compared to background stations (410.21 ± 0.2 ppm at MNM and 409.73 ± 0.23 ppm at WLG), AMY had higher mean values with higher variations (422.95 ± 0.54 ppm). All error ranges in the results indicate a 95% confidence interval on the mean. CO₂ levels measured at AMY include the effect from surrounding countries in addition to those from the local region, therefore, it was somewhat difficult to differentiate the differences in ΔCO₂ and ΔCO due to the COVID-19 lockdown in China from noise.

To focus on the effect of lockdown in China, ΔCO₂ and ΔCO in air parcels from China during the lockdown were compared with values from the same period in the previous 2 years (figure 4). Figure 4(a) shows the time series of all data of ΔCO₂ and ΔCO measured at AMY during the REF and LOCK periods, regardless of the inflow path of air parcels. The average ΔCO₂ during LOCK (13.9 ± 0.5 ppm) was similar to that during the REF period (14.1 ± 0.4 ppm). ΔCO₂ did not decrease during the LOCK period compared to the REF period, despite the COVID-19 lockdown. Unlike ΔCO₂, the average ΔCO during the LOCK period (168.8 ± 6.2 ppb) was lower than that during the REF period (231.8 ± 6.4 ppb).

Triangles in figure 4(a) shows the cases for air parcels originating from China classified based on the WRF-STILT modeling results. Using these cases, the average ΔCO₂ and ΔCO during the REF and LOCK periods were compared, and the monthly differences were analyzed (figure 4(b)). Air parcels from China had lower ΔCO₂ and ΔCO during the LOCK period relative to the REF period, and the differences between REF and LOCK periods were relatively small in February and significantly greater in March (see supplementary note 1).

The result from daily-averaged ΔCO₂ and ΔCO (no autocorrelation) between the REF and LOCK periods in supplementary figure 2 had no significant differences in the main findings in figure 4(b). The daily-averaged ΔCO₂ values during the REF and LOCK periods were 10.15 ± 2.17 ppm and 7.43 ± 1.08 ppm, respectively (supplementary figure 2). For daily-averaged ΔCO, their mean values showed 203 ± 56.8 ppb and 98.5 ± 28.4 ppb during the REF and LOCK periods, respectively. Two-sided t-tests showed that the differences in both daily-averaged ΔCO₂ and ΔCO between the REF and LOCK periods were statistically significant (α = 0.05). The p-values obtained for ΔCO₂ and ΔCO were 0.029 and 0.002 between REF and LOCK periods, respectively. Although ΔCO₂ in February did not show a statistically significant difference (p > 0.05), both ΔCO₂ and ΔCO significantly decreased in March during the LOCK period (p < 0.05).

The changes in ΔCO₂ and ΔCO responses to COVID-19 in February and March could be influenced by meteorology. North China, including Beijing, experienced air stagnation caused by decreased wind speed and declined PBL height during the city lockdown from 23 January to 13 February 2020 (Le et al 2020). Air stagnation in China may explain the greater decrease in ΔCO₂ and ΔCO in March compared to those in February 2020, when the emission decrease was larger. The asymmetric changes between the 2 months are consistent with the satellite data results. The monthly average ΔCO in Beijing in 2020 was 6.3% and 18.0% lower in February and March, respectively, compared to that in 2019 (Cai et al 2021). The similarity between our results and those of previous studies confirms that the effect of emission reductions from China due to COVID-19 could be detected through atmospheric observations at AMY.

3.2. Changes in ΔCO₂ and ΔCO in air parcels from different Chinese source regions

There are significant differences in emission characteristics within China, depending on the region. East China has more major cities, including Beijing, Tianjin, and Shanghai, and industries than Northeast China. East China’s GDP was three times higher on average than that of Northeast China in 2019 (Statista 2021). To compare and contrast the changes in ΔCO₂ and ΔCO at AMY depending on regional differences in emission characteristics, cases which were influenced by surface fluxes in China are separated...
into two different regions: East China and Northeast China (figure 3). Data where air parcels were found to be of Chinese origin but were not classified as being from the East or Northeast China were excluded from this analysis.

Figure 5 shows the average $\Delta$CO$_2$ and $\Delta$CO values for air parcels originating from East China and Northeast China during the REF and LOCK periods. The number of affected samples from Northeast China, compared to that from East China, was 1.5 times more during the REF period and three times more during the LOCK period. On average, during the REF period, $\Delta$CO$_2$ was higher for East China ($11.9 \pm 2.3$ ppm) than that for Northeast China ($7.7 \pm 0.7$ ppm). During the REF period, $\Delta$CO had a higher value when air parcels originated from East China than from Northeast China ($241.5 \pm 51$ ppb for East China and $150.9 \pm 27.5$ ppb for Northeast China). The higher $\Delta$CO$_2$ and $\Delta$CO in air parcels originating from East China during the REF period can be attributed to higher emissions from this area, which has more than three times the carbon emissions of Northeast China. According to national statistics for Chinese provinces, estimated carbon emissions were $3857.93$ Mt CO$_2$ for East China and $1085.5$ Mt CO$_2$ for Northeast China in 2017 (Shan et al 2020).

When compared to that during the REF period, the average $\Delta$CO$_2$ during the LOCK period decreased when originating from East China ($6.6 \pm 0.9$ ppm) but did not decrease when originating from Northeast China ($7.7 \pm 0.9$ ppm). Compared to the REF period, $\Delta$CO during the LOCK period decreased regardless of the source region, as $85.4 \pm 29.5$ ppb for East

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**Figure 4.** Comparison of $\Delta$CO$_2$ and $\Delta$CO between the REF and LOCK periods. (a) Time series of $\Delta$CO$_2$ (top) and $\Delta$CO (bottom) from February to March for 2018–2020. Orange lines and triangles are $\Delta$CO$_2$ ($\Delta$CO) values for averaged data from 2018 and 2019, and for air parcels originating from China during the REF period (February to March 2018 and 2019), respectively. Gray lines and triangles are $\Delta$CO$_2$ ($\Delta$CO) values for all data, and for air parcels originating from China during the LOCK period (February to March 2020), respectively. (b) $\Delta$CO$_2$ (left) and $\Delta$CO (right) during REF and LOCK periods for air parcels originating from China. The error bars indicate the 95% confidence intervals on the mean of the population. The white numbers in bars indicate the number of data used.
China and 110.7 ± 21.9 ppb for Northeast China. The reduction rate between REF and LOCK periods was more dominant when the air parcels originated from East China for both ∆CO2 and ∆CO. For East China, the reduction rates in ∆CO2 and ∆CO were approximately −44% and −65%, respectively. The East China reductions are beyond the 95% confidence intervals and statistically significant from the two-sided t-test ($p < 0.05$). The changes in ∆CO2 and ∆CO for Northeast China were +1% ($p > 0.05$) and −27% ($p > 0.05$), respectively.

The results presented here (figure 5) are in agreement with previous studies, which observed noticeable decreases in pollutant concentrations (NO2, PM2.5, and CO) in East China, which includes the North China Plain, compared to Northeast China, according to in situ data obtained within China or satellite data (Huang and Sun 2020, Wang et al 2020b, Hammer et al 2021). East China, which is economically active and carbon-intensive, was more affected by the COVID-19 lockdown than Northeast China, resulting in similar ∆CO2 and ∆CO between the two regions during the LOCK period. Though it has not been extensively reported in recent China-focused studies, these results suggest that each region in China may have a different atmospheric CO2 reduction due to COVID-19.

### 3.3. Changes in emission characteristics due to lockdown

The ∆CO/∆CO2 ratio refers to the proportion of emitted CO relative to emitted CO2 from the same anthropogenic combustion sources. It can be used to distinguish the source region/type and for estimating the combustion efficiency (Suntharalingam et al 2004, Wang et al 2010, Turnbull et al 2011a, Tohjima et al 2014, Niu et al 2018, Tang et al 2018, Lee et al 2020, Sim et al 2020). A higher ∆CO/∆CO2 ratio indicates that the source regions have incomplete combustion, and that most of the source types are domestic coal and biofuel combustion, with low contributions of vehicles with catalytic converters. The ∆CO/∆CO2 ratio comparison for air parcels from China and South Korea during the REF period was conducted as per supplementary note 3. The ratio for China was twice that of South Korea because of their use of biomass and domestic coal which emit more CO and have relatively low combustion efficiency. When compared with the ∆CO/∆CO2 ratios determined in previous studies, the ratio found in the present study for China was lower due to improvements in combustion efficiency and strict CO emission controls in recent years.

To investigate the changes in emission characteristics in China due to COVID-19, the ratios of ∆CO to ∆CO2 between REF and LOCK periods were compared (figure 6). The ∆CO/∆CO2 ratio indicates the slope of the reduced major axis regression between ∆CO2 and ∆CO. The ∆CO/∆CO2 ratios were $24.81 ± 0.88$ ppb ppm$^{-1}$ ($r = 0.92$) and $24.75 ± 2.5$ ppb ppm$^{-1}$ ($r = 0.67$) during the REF and LOCK periods, respectively, and the difference in ratios was not significant ($p > 0.05$). This suggests that emission characteristics, such as emission sources and combustion efficiency, might not change despite the significant decrease in ∆CO2 and ∆CO during the LOCK period. That is, the significant decrease in in ∆CO2 and ∆CO during the LOCK period is due to the effect of the reduction of emissions due to COVID-19. The reduction in the high enhancement cases for both ∆CO2 and ∆CO during the LOCK period (figure 6) also supports this implication.
4. Discussion and conclusion

Due to social restrictions during the first COVID-19 pandemic period in 2020, CO\textsubscript{2} emissions in China sharply decreased, leading to expectations that the atmospheric CO\textsubscript{2} level can be diminished. However, studies using satellite data to measure column-averaged dry-air mole fractions of CO\textsubscript{2} have failed to detect any significant reductions (Chevallier \textit{et al} 2020, Sussmann and Rettinger 2020, Buchwitz \textit{et al} 2021, Cai \textit{et al} 2021). Instead, only ground-based observations near South China have found a significant reduction in the $\Delta$CO$_2$/$\Delta$CH$_4$ ratios (Tohjima \textit{et al} 2020). Although there have been several attempts to determine the decrease in atmospheric CO\textsubscript{2} levels due to COVID-19, the rapid atmospheric mixing in the Northern Hemisphere dilutes the signal with the ‘noise’, making it difficult to detect the signal of reduced emissions.

Despite these difficulties, the present study detected a significant reduction in the short-term regional enhancement of the observed atmospheric CO\textsubscript{2} during the first COVID-19 pandemic period in 2020. We were able to verify the impact of the entire Chinese continent by using observations at a regional monitoring station in South Korea, an area downwind of China. Because the CO\textsubscript{2} background levels continued to increase, CO\textsubscript{2} enhancements above the background level were used to capture the changes from recent anthropogenic emissions during the COVID-19 lockdown. The WRF-STILT model was then applied to isolate the influence of China while minimizing the effect of rapid atmospheric transport in the Northern Hemisphere. The $\Delta$CO/$\Delta$CO\textsubscript{2} ratio was utilized to identify changes in China’s emission characteristics due to COVID-19. Although vegetation activity and soil respiration in winter might have negligible effects on the variation in CO\textsubscript{2} levels, further studies using process-based models are needed to evaluate the possible effects of vegetation activity and soil respiration on the observed CO\textsubscript{2} variations.

When affected by air parcels from China, $\Delta$CO\textsubscript{2} decreased on average by $-1.92 \pm 0.03$ ppm in 2020, particularly by $-3.61 \pm 0.06$ ppm in March, compared to the same period in 2018 and 2019. According to Tohjima \textit{et al} (2020), a 10% global CO\textsubscript{2} emissions reduction results in approximately a $-0.5$ ppm decrease in atmospheric CO\textsubscript{2}. The estimated reductions in CO\textsubscript{2} emissions in China from previous studies were $-18.4\%$ and $-9.2\%$ in February and March 2020, respectively (Liu \textit{et al} 2020). The reason why the atmospheric $\Delta$CO\textsubscript{2} reduction in this study is a large response to the emission reduction may be because this study targets China, which experienced the greatest emission reductions worldwide. The $\Delta$CO\textsubscript{2} decreased sharply in East China compared to Northeast China, indicating that the eastern region had a significant impact on $\Delta$CO\textsubscript{2} in China. These results were similar when using MNM or WLG as the background station because the enhancement of AMY is heavily influenced by regional and local signal.

Although the average global atmospheric CO\textsubscript{2} level is still increasing, this study revealed the atmospheric impact of COVID-19 lockdown-induced carbon emission reductions in China, suggesting that the CO\textsubscript{2} level might decrease or increase at a much slower rate if substantial emission reductions are achieved.
in multiple nations. The reduction of human activity to address the COVID-19 pandemic clearly illustrates how the increase in atmospheric CO₂ levels can be controlled, which is a major factor in directly mitigating climate change.

Data availability statement

The data that support the findings of this study are available upon reasonable request from the authors.

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Conflict of interest

The authors declare no conflicts of interest.

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