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Authors
Liu, Zhu
Ciais, Philippe
Deng, Zhu
et al.

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COVID-19 causes record decline in global CO2 emissions

Zhu Liu[1*], Zhu Deng[1], Philippe Ciais[2], Ruixue Lei [3], Steven J. Davis[4], Sha Feng[4], Bo Zheng[2], Duo Cui[1], Xinyu Dou[1], Pan He[1], Biqing Zhu[1], Chenxi Lu[1], Piyu Ke[1], Taochun Sun[1], Yuan Wang[5,6], Xu Yue[7], Yilong Wang[2], Yadong Lei[8], Hao Zhou[8], Zhaonan Cai[9], Yuhui Wu[10], Runtao Guo[11], Tingxuan Han[12], Jinjun Xue[13, 14, 15], Olivier Boucher[16], Frederic Chevallier[2], Eulalie Boucher[2], Yimin Wei[17], Qiang Zhang[1], Dabo Guan[1], Peng Gong[1], Daniel M. Kammen[18], Kebin He[10], Hans Joachim Schellnhuber[19]

[1] Department of Earth System Science, Tsinghua University, Beijing 100084, China.
[2] Laboratoire des Sciences du Climate et de l'Environnement LSCE, Orme de Merisiers 91191 Gif-sur-Yvette, France
[3] Department of Meteorology and Atmospheric Science, The Pennsylvania State University, University Park, PA 16802
[4] Department of Earth System Science, University of California, Irvine, 3232 Croul Hall, Irvine, CA 92697-3100, USA
[5] Division of Geological and Planetary Sciences, California Institute of Technology, Pasadena, CA, USA
[6] Jet Propulsion Laboratory, California Institute of Technology, Pasadena, CA, USA
[7] Jiangsu Key Laboratory of Atmospheric Environment Monitoring and Pollution Control, Collaborative Innovation Center of Atmospheric Environment and Equipment Technology, School of Environmental Science and Engineering, Nanjing University of Information Science & Technology (NUIST), Nanjing 210044, China
[8] Climate Change Research Center, Institute of Atmospheric Physics, Chinese Academy of Sciences, Beijing 100029, China
[9] Key Laboratory of Middle Atmosphere and Global Environment Observation, Institute of Atmospheric Physics, Chinese Academy of Sciences, Beijing 100029, China.
[10] School of Environment School, Tsinghua University, Beijing 100084, China
[11] School of Mathematical School, Tsinghua University, Beijing 100084, China
[12] Department of Mathematical Sciences, Tsinghua University, Beijing 100084, China
[13] Center of Hubei Cooperative Innovation for Emissions Trading System, Wuhan, China
[14] Faculty of Management and Economics, Kunming University of Science and Technology, 13 Kunming, China
[15] Economic Research Centre of Nagoya University, Furo-cho, Chikusa-ku, Nagoya, Japan
[16] Institute Pierre-Simon Laplace, Sorbonne Université / CNRS, Paris
[17] Center for Energy and Environmental Policy Research, Beijing Institute of Technology, Beijing, China
[18] University of California, Berkeley, CA, USA
[19] Potsdam Institute for Climate Impact Research, 14412 Potsdam, Germany

Corresponding author: zhuliu@tsinghua.edu.cn

The unprecedented cessation of human activities during the COVID-19 pandemic has affected global energy use and CO_2 emissions. Here we show that the decrease in global fossil CO_2 emissions during the first quarter of 2020 was of 5.8% (542 Mt CO_2 with a 20% 1-σ uncertainty). Unlike other emerging estimates[1], ours show the temporal dynamics of emissions based on actual emissions data from power generation (for 29 countries) and industry (for 73 countries), on near real time activity data for road transportation (for 132 countries), aviation and maritime transportation, and on heating degree days for commercial and residential sectors emissions (for 206 countries). These dynamic estimates cover all of the human induced CO_2 emissions from fossil fuel combustion and cement production. The largest share of COVID-related decreases in emissions are due to decreases in industry (157.9 Mt CO_2, -7.1% compared to 2019), followed by road transportation (145.7 Mt CO_2, -8.3%), power generation (131.6 Mt CO_2, -3.8%), residential (47.8 Mt CO_2, -3.6%), fishing and maritime transport (35.5Mt CO_2, -13.3%) and aviation (33.4 Mt CO_2, -8.0%). Regionally, decreases in emissions from China were the largest and earliest (-10.3%), followed by Europe (EU-27 & UK) (-4.3%) and the U.S. (-4.2%). Relative decreases of regional CO_2 emissions are consistent with regional nitrogen oxides concentrations observed by satellites and ground-based networks. Despite the unprecedented decreases in CO_2 emissions and comparable decreases in economic activities, we monitored decreases in the carbon intensity (Emission per unit of GDP) in China (3.5%), the U.S. (4.5%) and Europe (5.4%) over the first quarter, suggesting that carbon-intensive activities have been disproportionally impacted. ***[262 words]***

COVID-19 has caused hundreds of thousands of deaths worldwide since December of 2019, together with large-scale ongoing reductions in human activities and profound effects on different national economies. Industrial production and energy consumption in some countries were reported to decline by up to 30% in just a few weeks[2,3] as lockdowns were imposed to protect public health. Fossil fuel and cement CO_2 emissions are directly linked to human activities. Initial estimates of emissions changes based on a limited sample of power plants and indirect satellite observations of atmospheric pollutants[4,5] have suggested that we may be witnessing the largest drop of emissions since the end of the Second World War. However, quantitative analyses of the pandemic's effects on energy use and CO_2 emissions for all key sectors are still lacking[1,6]. A major limitation is that detailed inventories of energy and fuel use that have historically been used to assess CO_2 emissions are only available with a lag of one or two years[7-12]. Here, we compile and analyze high-frequency and up-to-date electricity-related emission data, emission estimates by the industry, along with online data-streams of human activity that are closely related to emissions in order to provide a near real time assessment of the impacts of the COVID-19 pandemic on country- and sector-specific CO_2 emissions during the first quarter of 2020 and to enable a monitoring of how CO_2 emissions will change in the following period.

Details of our data sources and analytic method are provided in the *Methods* section. In summary, we calculate regional CO_2 emissions between January and April 2020 and compare them to the same period in 2019, drawing on hourly datasets of electricity power production and CO_2 emissions in 29 countries (including the substantial variations in carbon intensity associated with electricity production), three different indexes of daily vehicle traffic / mobility in 416 cities worldwide, monthly production data for cement, steel and other energy intensive industrial products in 73 countries, daily maritime and aircraft transportation activity data, as well as proxies for the residential and the commercial building emissions (see Extended Data Table 1 for data sources). Together, these data cover almost all fossil and industry sources of global CO_2 emissions. It is important to note that during the winter, CO_2 emissions from the power sector, as well as from residential and commercial buildings are highly sensitive to temperature (i.e. heating degree days-HDD[7]). The first months of 2020 were exceptionally warm across much of the northern hemisphere, meaning that 2020 CO_2 emissions would have been somewhat lower than the same period in 2019 even without the disruption in economic activities and energy production caused by COVID-19 and related lockdowns.

Figure 1 shows estimated trends in total CO_2 emissions globally and in several major regions. Globally, we find a global 5.8% decrease of CO_2 emissions during the first quarter (Q1) of 2020 (solid black curve) compared with the same period in 2019 (dashed black curve). The most pronounced decline occurred in China, where first quarter emissions fell by -10.3%, with substantial but progressively smaller decreases in Europe (EU27 & UK, Figure 1 shows five countries, full numbers see Source Data) (-4.3%), Japan (-4.3%), the U.S. (-4.2%), Brazil (-4.1%), Russia (-3.0%), and India (-1.6%). The large and early drop in Chinese emissions correspond to an early outbreak of COVID-19 and strict lockdown measures, which were relaxed throughout March. Consequently, the 2020-2019 difference in China's emissions were much less in March (-7.8%) than in February (-19.3%). In other countries, decreases in emissions due to COVID-19 weren't apparent until late February or March, coincident with the onset of lock-downs in different countries, with greater decreases generally observed in March (U.S.:-8.5%, EU27 & UK: -6.5%, India: -12.7%, Brazil:-10.7%, Japan -4.4%) than in February (U.S.: 1.1%, EU27 & UK: 0.4%, India: 6.4%, Brazil: 1.6%, Japan -1.1%).

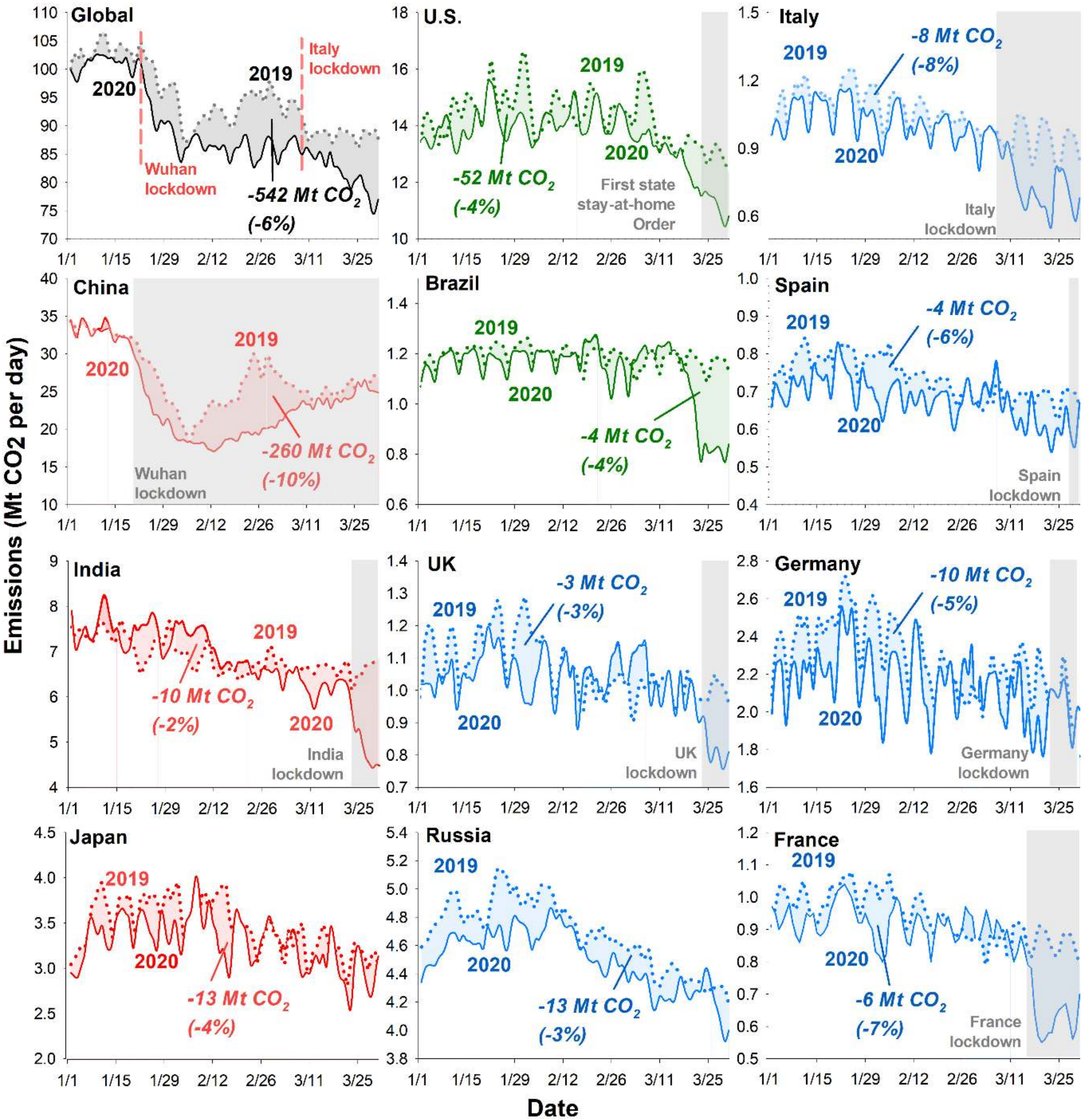

Figure 1. Daily CO_2 emissions in the first quarter of 2019 (dotted line) and 2020 (Solid Line) for the world, U.S., Italy, China, Brazil, Spain, India, UK, Germany, Japan, Russia and France. Different color for countries represents different continents.

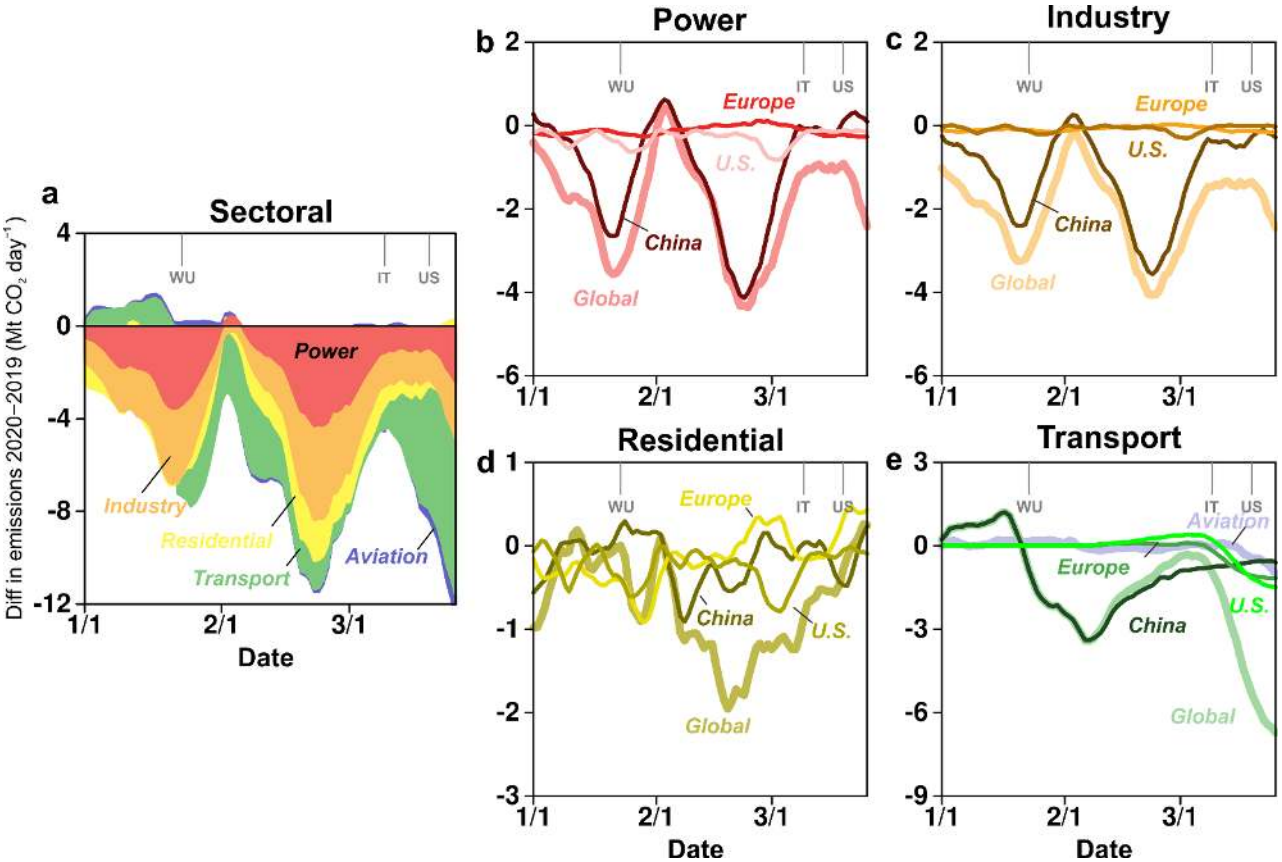

Figure 2 | (a) Global fossil fuel and cement CO_2 emissions (Seven-days running mean) difference between 2020 and 2019 for different sectors. (b-e) Emissions differences for different sectors for different regions. The green lines for the transport sector are for ground (mainly road) transport emissions and the light blue line is for aviation emissions changes for the entire globe.

Figure 2 shows the breakdown of emissions decreases by sector. The largest contributions to the global decrease in emissions come from industry (-157.9 Mt CO_2, 29% of the total Q1 decrease; orange in Fig. 2a) and road transportation (-135.7 Mt CO_2, 25% of the total; green in Fig. 2a), with decreases from power sector just slightly less (-131.6 Mt CO_2, 24% of the total;

red in Fig. 2a), and relatively small decreases in residential emissions (-47.8 Mt CO_2, 9% of the total; yellow in Fig. 2a). The rest of the reduction comes from aviation, ships emissions.

Power Generation

Our estimates of power sector emissions rely on near real time hourly data (except for China and Japan where only monthly data are available, SI Figure 1) of electricity production and the carbon content of the electricity mix. Thus, we are able to resolve the effects of weather-driven variations of renewable electricity supply (See *Methods* for temperature adjustment) as well as the increases in natural gas relative to coal for power generation in 2020 in the U.S. that has been caused by very low oil prices. Figure 2b shows that in the first quarter of 2020, global CO_2 emissions from the power sector declined by -3.8% (-131.6 MtCO_2), with a large decline in China (-6.8%, -76.2 MtCO_2) and somewhat smaller decreases in the U.S. (-4.9%, -21.7 MtCO_2) and the EU-27 & UK (-3.0%, -8.5 MtCO_2). Some of the drop in China's power sector emissions are due to prevailing warmer winter temperatures, and the near-zero differences in late January and early February between 2020 and 2019 are because this was when the country's spring festival occurred in 2019 (Fig. 1). Meanwhile, power emissions in India were stable in the first quarter of 2020 (+1.0%, +3.0 Mt CO_2) (See Source Data Tables 2.1 and 2.2). However, a sharp decrease of CO_2 emissions from the power sector in India (-8.7%) occurred in March, when this country adopted lock-down measures.

Industry and cement production emissions

Industry emissions from steel, chemicals and other manufactured products from fossil fuel combustion and the cement production process represent on average 29% of the global CO_2 emissions, with a much larger share of national emissions in developing countries (39% in China and 33% in India)[13]. We collected data separately for steel, chemicals (based on 8 chemical products) and 26 other industrial products, as well as for cement production in China, and data for steel and cement production in India, for a better attribution of industrial CO_2 emissions changes (SI Data Table 4.1-4.5). Only emissions from direct fuel consumption and chemical process emissions by the industry sector were considered, electricity related emissions for the industry being already counted in the power generation sector. In the first quarter of 2020, global industry emissions fell by -4.9% in most countries, including China (-10.1%, -81.7 MtCO_2), U.S. (-2.7%, -4.9 MtCO_2), EU27 & UK (-4.4%, -6.4 MtCO_2) and India (-7.5%, -15.5 MtCO_2) (Figure

3, SI Data Table 4.1-4.5). In China, emissions from steel production (41.6% of national industrial emissions from fuel combustion) increased by +1.4% and +5.0% in January and February, and then dropped by -1.7% in March, compared to 2019. Despite the COVID-19 pandemics, emissions from the steel industry thus remained 1.4% larger in the first quarter of 2020. For the cement industry (30% of China's industrial emissions from fuel combustion), official reports of National Statistics[14] show a huge decline of -23.9% in the first quarter in 2020, namely -29.5% in January and February together, and -18.3% in March. Emissions from the production of chemicals in China also decreased by -4.2%, while emissions from other industries have fell by -13.6%. In India, the emissions from steel production (47% of national industrial emissions from fuel combustion) decreased by -5.3% in the first quarter in 2020, with a big drop of -13.9% in March. Emissions from fuel combustion in cement industry decreased by -10.2%, thus less than in China. Global emissions from the decomposition of calcium carbonate during cement production have significantly dropped in the first quarter in 2020 by -20.4% (-48.2 Mt CO_2), with the largest contribution from China (-23.6%, 26.9 Mt CO_2) and India (-10.16%, 3.6 Mt CO_2).

Ground transportation emissions

Emissions from ground transportation (SI Figure S4) were calculated based on Google Mobility Reports, Baidu Migration Scale Index and TomTom congestion level with daily transportation activity data for 132 countries and 416 global cities (See Methods and SI Data Table 3.1-3.3). Ground transportation (See Methods for data and calculation process) contributes 19% of the world CO_2 emissions and decreased dramatically by -8.3% in Q1 (-135.7 MtCO_2) thus contributing 25% of the decline of the emissions from all sectors (Figure 2). In China, even though cities started locking down in the last week of January, the average emissions from transport during that month increased yet by 7.4% in January due to an earlier start of the Spring Festival travel rush (Jan. 10th) compared to 2019 (Jan. 21st). In February, ground transport emissions dropped abruptly by -75.1% and continued to decrease by -34.2% in March, compared to the same month in 2019. The emission from ground transport dramatically decreased in other countries just after lockdown measures in March. Ground transport emissions in U.S. and India dropped by -10.0% and -22.9% in March, respectively. Emissions in European countries dropped by -22.8% in March, with Italy and Spain showing the largest reductions of -48.3% and -37.6% respectively (SI Figure S4).

Aviation and ships emissions

Emissions from global aviation decreased by 8% during Q1 (-33.4MtCO_2), among which those from international aviation decreased by -19.8MtCO_2 (SI Figure S5). Domestic aircraft emissions are included in our global estimates, but only international aviation emissions were attributed to different countries (See Methods for data and calculation process). The total number of flights and global aviation emissions shows two consecutive decreases, one by the end of January in Asia and another from March 15th to 30th in the rest of the world. By the end of March, there was 85% less flights than during the same period in 2019 (SI Figure S5). Emissions declined sharply after mid-March, coincident with travel bans and lock-down measures.

Global CO_2 emissions from fishing and international shipping (see Methods for data and calculation process) decreased by -13.3% (-35.4 Mt CO_2) in Q1. Specifically, emissions from container and bulk carrier ships decreased by -15% and -25.8%, while those from oil tankers increased by +2.2% possibly owing to countries importing more cheap oil. Emissions from 19 other 19 ship classes including fishing, show a reduction of -11.5%.

Commercial and Residential buildings

We estimated that emissions from commercial and residential buildings declined by 3.6% in the first quarter of 2020 compared to the same period in 2019. This sector is the one for which emission changes have the largest uncertainty, as there is no actual fuel use data worldwide. The emissions from fuel use (oil and gas) in commercial and residential buildings was estimated using population-weighted heating degree days by the ERA5[15] reanalysis of 2 meters air temperature for 206 countries. We found that the global heating demand in Q1 declined by -5.0% compared to 2019, owing to the abnormal warm northern-hemisphere winter[16], resulting in the decreased of emissions. Note that the effect of increased time spent in households on emissions was not accounted for.

Our estimates of decreases in fossil and industry CO_2 emissions (See Methods and SI Table S9) are consistent with observed changes in nitrogen dioxide (NO_2) emissions, which are also mainly produced by fossil fuel combustion. Tropospheric NO_2 column concentration data from satellites[17,18], and surface NO_2 concentrations from air quality stations show a decrease (See *Methods*, SI Figures S7 and SI Table 2) consistent with the reduction of fossil carbon fuels emissions presented above. Overall, NO_2 decreased over China in the first quarter of 2020 is consistent with our calculated NO2 emission declines based on near real time activity and emission data (See Methods and SI Table S9),) . Over the U.K., France, Germany, and Italy, NO_2 decreased by a similar amount than in the U.S.. Over India, NO_2 showed a weaker decline, also consistent with satellite data.

Overall, NO_2 declines in January and February over China are the largest declines since the OMI data become available in 2004 (SI Figure S10). The consistent results from both ground based and satellite monitoring systems confirm the significant decline of the NO2 concentrations due to COVID-19(See Methods). Based on the OMI satellite data, Over the U.K., France, Germany, and Italy, NO_2 decreased by a similar amount than in the U.S.. Over India, NO_2 showed a weaker decline, also consistent with satellite data.

It is still unclear to what extent annual CO_2 emissions will be continue to be affected by the COVID-19 pandemic, which will depend on the efficacy and stringency of public health policies and the recovery of economies and human activities around the world. The IMF predicts that the global annual economic output (GDP) will decrease by -3.0% in 2020, which is worse than the financial crisis in 2008 [19], and yet this projection was based on the assumption that the COVID-19 epidemics will fade globally in the second half of this year. Based on near real time activity and emission data, we estimate a decrease of 5.8% (542 MtCO2) of global CO2 emissions in Q1 of 2020, the largest global quarterly emission decrease ever recorded, larger than during the 2009 economic crisis. This signal reflects unprecedented impacts of the pandemics on the global economy. Nevertheless, given negative impacts on the carbon intensive industry sector such as cement production, we inferred improvements of the ratio of the emission intensity (CO2 emissions per unit of GDP) in China (3.5%), US (4.5%) and Europe (1.8%), although such improvement are the consequence of highest-ever cost payed for the reduction of 1t of CO2 - between 1k and 10k US$ per ton, it still suggesting a unique opportunity for green investments and low carbon development in the years to come, for which global concerted efforts will urgently be needed. The ability to monitor trends in emissions in near real time that we demonstrate here will be invaluable in adaptively managing the transition.

Methods

CO_2 emission in baseline year 2019

The CO_2 emissions and sectoral structure in 2018 for countries and regions are extracted from EDGAR V4 3.2[10], and the emissions are scaled to the year 2019 based on the growth rates from Liu et al.[20] and the Global Carbon Budget 2019[21]. For countries with no current estimates of emission growth rates in 2019 such as Russia, Japan and Brazil, we assume their growth rates of emissions were 0.5% based on the emission growth rates of rest of world [21].

Given the large uncertainty of CO_2 emission in China[22,23], we calculated CO_2 emissions based on the methodology developed[24] previously:

$$\text{Emissions}= \sum\sum\sum(Energy\ consumption\ data_{i,j,k} \times Emission\ factors_{i,j,k}) \quad (1)$$

i, j, k reflect the regions, sectors and fuel types respectively. In our calculation, i covers XX countries that representing 70% of global total emissions. j covers four sectors that are power generation, industry, transportation and household consumption, k covers three primary fossil fuel types which are coal, oil and natural gas. Emission factors can be further separated into the net heating values for each fuel "v", the energy obtained per unit of fuel (TJ per t fuel), the carbon content "c" (t C TJ-1 fuel) and the oxidization rate "o", which is the fraction (in %) of fuel oxidized during combustion and emitted to the atmosphere.

$$\text{Emission} = \sum\sum\sum(Energy\ consumption\ data_{i,j,k} \times v_{i,j,k} \times c_{i,j,k} \times o_{i,j,k})$$

We assumed that the emission factors and the structure remain unchanged for each country in 2020 when comparing with 2019. Thus, the rate of change of the emission is calculated based solely on the change of the energy consumption data in Q1 of 2020 compared to Q1 of 2019.

Based on the assumption of sectoral carbon intensity and energy structure remain unchanged from 2018, the EDGAR sectors were aggregated into four main sectors, including power sector, transport sector, industry sector and residential sector. We used actual near-real time emissions data for the power sector, industry emission data (including cement), and scaled CO_2 emissions to 2020 by using proxy data for other sectors. We include in the estimate of global emissions those from domestic and international aviation and shipping.

Power sector.

For China, only monthly electricity generation statistics are available on the National Bureau of Statistics in China (http://www.stats.gov.cn/tjsj/). Then the electricity generation data were disaggregated to daily emission data by the daily coal consumption of six main power company (https://www.wind.com.cn/). For Japan, we collect the daily electricity generation data from 10 electricity companies in Japan (Hokkaido Electric Power, Tohoku Electric Power Network, Tokyo Electric Power Company, Chubu Electric Power Grid, Hokuriku Electric Power Transmission & Distribution Company, Kansai Electric Power, Chugoku Electric Power Company, Shikoku Electric Power Company, Kyushu Electric Power and Okinawa Electric Power Company). For US, we used daily total electricity generation data of 48 states from Energy Information Administration's (EIA) Hourly Electric Grid Monitor (https://www.eia.gov/beta/electricity/gridmonitor/). For EU countries and UK, electricity generation data every 15 minutes by production types are collected from ENTSO-E Transparent platform (https://transparency.entsoe.eu/dashboard/show) and near real time variations of the carbon content of electricity was taken from Electricity Map (https://www.electricitymap.org/). Due to the poor data quality or missing data, Croatia, Cyprus, Ireland, Luxembourg and Malta are excluded from the calculation. The hourly data of the other 23 EU countries (including Austria, Belgium, Bulgaria, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Italy, Latvia, Lithuania, Netherlands, Poland, Portugal, Romania, Slovakia, Slovenia, Spain, Sweden) and United Kingdom are aggregated into daily total electricity generation data. For India, daily total electricity generation data are updated by Power System Operation Corporation Limited (https://posoco.in/reports/daily-reports/). For Russia, daily electricity generation data are collected from United Power System of Russia (http://www.so-ups.ru/index.php). For Brazil, daily electricity generation data are downloaded from the Operator of the National Electricity System (http://www.ons.org.br/Paginas/). All the daily electricity generation data are further aggregated into monthly data to calculate the monthly growth rates. We use the linear regression between electricity consumption and daily temperature in the winter of 2018 and 2019, and correct temperature effect to the electricity generation in 2020. For the monthly emissions in 2019, we use the monthly electricity generation for countries to allocate the emissions in power sector for each month. Then we calculate the monthly emissions in 2020 based on the monthly growth rates compared to the same periods in 2019.

Industry and cement production.

For China, the industrial sector is divided into four industries including steel industry, cement industry, chemical industry, and other industry based on the structure of industrial emissions calculated by IEA[25] data. For the steel industry, we collect the global monthly crude steel production data from World Steel Association (https://www.worldsteel.org/). For cement industry, China's monthly cement production data are available on the National Bureau of Statistics. We estimate the growth rate of chemical production in China chemical industry by calculating the average cumulative growth rates of sulfuric acid, caustic soda, soda ash, ethylene, chemical fertilizer, chemical pesticide, primary plastic and synthetic rubber. For other industry, we estimate the change in China other industry by calculating the average cumulative growth rates of 26 industrial products (crude iron ore, phosphate ore, salt, feed, refined edible vegetable oil, fresh and frozen meat, milk products, liquor, soft drinks, wine, beer, tobaccos, yarn, cloth, silk and woven fabric, machine-made paper and paperboards, newsprint, plain glass, ten kinds of nonferrous metals, refined copper, lead, zinc, electrolyzed aluminum, industrial boilers, metal smelting equipment, and cement equipment). Based on the emission distribution of these four industries in industrial sector in China, we finally get the annual growth rate of industrial sector in China.

For US and Russia, we use the cumulative Industrial Production Index (IPI) from Federal Reserve Board (https://www.federalreserve.gov) and Federal State Statistics Service (https://eng.gks.ru) respectively, to estimate the growth rates of the emissions in these countries.

For India, the industrial sector is divided into steel industry, cement industry, and other industry. Emissions from steel industry and cement industry account for 60% of the total emissions in industrial sector of India. The steel production in India is extracted from World Steel Association. India's monthly cement production data could be found from the Office of the Economic Advisor, but the last observation was on February. We assume that the cement production in India has dropped 40% in March. For other industry, we assume the growth rate is the average of growth rates of steel production and cement production.

For Europe (EU27 & UK), Japan and Brazil, we use the cumulative Industrial Production Index (IPI) to estimate the growth rates of emissions in these countries or regions, collected from Eurostat (https://ec.europa.eu/eurostat/home), Ministry of Economy, Trade and Industry (https://www.meti.go.jp), and Brazilian Institute of Geography and Statistics (https://www.ibge.gov.br/en/institutional/the-ibge.htm) respectively. However, the last observation in EU27 and UK was in January 2020 and those in Japan, Russia and Brazil were in February 2020. To estimate the current growth in March 2020, for EU27 and UK, we assume that the monthly growth rate in February 2020 equals to that of the same month in 2019. The monthly growth rate in March 2020 in EU27 and UK together has fell 5%, based on the assumption of the average growth rate of industrial sector in China (-8.1%) and US (-2.2%) because of the implement of locking down policies later than China but earlier than US. For Japan and Brazil, as looser travel restriction in these countries, we assume the monthly growth rates in March were -3% compared to February. The monthly industrial emissions are allocated to daily emissions by electricity data.

For the emissions from chemical process during cement production, we only had access to data from China and India which nevertheless account for 63% of the global cement production and CO_2 emissions. We collected monthly cement production in China and India and calculated emissions from cement production by multiplying emission factors of cement production process as:

$$Emissions_{cement} = Production_{cement} \times Emission\ factors_{cement}$$

Ground transportation.

The mobility trends from the Google COVID-19 Community Mobility Reports (https://www.google.com/covid19/mobility/) are mainly used in this study. The mobility changes are calculated based on the visits and visit duration in six places categories, including grocery & pharmacy, parks, transit stations, retail & recreation, workplace, and residential. The daily mobility changes are compared to the median value during the first five weeks in 2020 for the corresponding day of the week as the baseline value. Except for residential, we consider that the mobility changes of visits in the other five places representing the total mobility, so we calculate the daily average mobility change of five of the place categories to represent as the changes of the total traffic volume in these countries, based on the assumption the mobility in the same period in 2019 and January in 2020 is at the same level of the baseline value. The average mobility of EU countries (except for Cyprus due to the lack of data) and UK is used to estimate the emission growth of Europe.

In China, we use the change of the Baidu Migration Scale Index to characteristic the change of transport sector, due to the lack of data in Google Community Mobility Reports in China. This index is aggregated from migration flows within the nation based on the positioning requests on Baidu Map services. The migration scale index is reported since Jan. 12th in 2019 and Jan. 1st in 2020, 9 days before the start of the Spring Festival travel rush every year. To fill the data gap between Jan. 1st 2019 to Jan. 11th, 2019, we use the average value of migration index between Jan. 12th, 2019 and Jan. 20th, 2019. Then we aggregate the daily index into monthly total and calculate the monthly changes in 2020 compared to 2019. In Russia, because the lack of data and the earliest lockdown policy implementing on Mar. 30th in Moscow, we assumed that the transport emissions remain unchanged in the first quarter in 2020.

In addition, we collected TomTom congestion global level data from TomTom website (https://www.tomtom.com/en_gb/traffic-index/). The congestion level represents the extra time spent on a trip, in percentage, compared to uncongested condition. TomTom congestion level data are available for 416 cities across 57 countries at a temporal resolution of 10 to 15 minutes. We compared the time series of TomTom congestion level in the first quarter of 2019 and 2020. The emission changes were first calculated for individual cities, and then weighted by city emissions to aggregate to national changes.

Aviation.

Although both the International Civil Aviation Organization (ICAO) and the International Air Transport Association (IATA) publish yearly statistics of aircraft operations, CO2 emissions from commercial aviation are usually reconstructed from bottom up emission inventories based on the knowledge of individual flights[26]. The International Council on Clean Transportation (ICCT)[27] published that CO_2 emissions of commercial aviation from international passenger movements totaled 444 Mt in 2018 and implied annual compound growth rate of total emissions from commercial flights, 5.7%, during the past five years from 2013 to 2018[1] . Sub-national CO_2 emissions from international passenger operations based on the location of flights departing airports are provided by ICCT[28]. It is known that total CO_2 emissions from all commercial operations include passenger movement, belly freight, and dedicated freight. ICCT published that passenger transport accounted for 81% of total emissions in 2018, so we use this proportion to estimate the international aviation emissions from commercial flights in 2018. Due to the lack of emissions data after 2018, we used a compound growth rate of commercial aviation emissions, 5.7%, to estimate the international aviation emissions from commercial flights in 2019. Based on the assumption that the number of international commercial flights and the number of total commercial flights including domestic and international flights have the same distribution over time, we collect the number of domestic commercial flights for each week in the first quarter in 2019 and the same week in 2020 from aviation worldwide Limited-OAG (https://www.oag.com/about-oag) to estimate international aviation emissions from commercial flights for each week during this period. Daily tracking statistics about commercial flights and total flights in 2020 are provided by Flightradar24 (https://www.flightradar24.com/51.5,-0.12/8), to estimate all aviation emissions in the first quarter in 2020. As processing such data will require some time, we mix different sources of information to gain a more rapid knowledge into the time evolution of CO2 emissions. For this we use daily statistics from AirNav/RadarBox published daily on their website (2019 and 2020). As these statistics are expressed as number of daily flights grouped by destinations, they are not sufficient to assess CO2 emissions and need to be combined with previous CO2 emission inventories for commercial aviation. Specifically we use the B1 2025 QUANTIFY emission inventory at monthly and 1°x1° resolution[28] and normalise it to the 918 Mt CO2/yr global emissions estimated by Graver et al. (2019)[26] for year 2018. This includes all commercial traffic (passenger and freight). We take this distribution to be also representative of year 2019. We then define 12 main regions of air traffic upon which we project the AirNav/RadarBox categories. For instance, the US box corresponds to a mix of the “US <-> US” and “US <-> NON US” categories; the North Atlantic flight corridor corresponds to the “US <-> Europe” category, etc. This mapping and the weight attributed to the different categories are somewhat arbitrary but this has limited impact on the results as all categories of traffic decrease sharply albeit with somewhat different timing. The 2019 emission inventory is then scaled from the 2019 inventory using weighted ratios of daily 2020 to monthly-mean daily 2019 flights for each corresponding category. A global daily CO_2 emission is then estimated from the spatially-distributed daily 2020 emission map (SI Figure S5).

Ships

The Third International Maritime Organization greenhouse gases study published global shipping CO_2 emissions from 2007-2012 [29]. We completed these data by global shipping CO_2 emissions during the period of 2013-2015 from the ICCT report [30]. In addition, IEA released international shipping CO_2 emissions from 2000 to 2018 (https://www.iea.org/reports/tracking-transport-2019/international-shipping). International shipping CO_2 emissions released by IEA were on average 23% lower than those published by IMO. We used this ratio to modify international shipping CO_2 emissions from IEA. According to the Third IMO GHG Study, CO_2 emissions from international shipping accounts for 87% of global shipping emissions, domestic and fishing accounts for 9% and 4%, respectively. We estimated global CO_2 shipping emissions from 2016-2018 with the modified IEA’s international emissions and the ratio between international shipping and global shipping emissions. And we extrapolated emissions from 2007-2018 to estimate emissions in 2019. We obtained emissions for the first quarter of 2019 based on the assumption that monthly variation is flat in shipping CO_2 emissions. In addition, we assume that the change in shipping emissions is linearly related to the change in ship’s volume. We collected the change in container ships (https://www.straitstimes.com/business/economy/coronavirus-global-container-shipments-set-to-fall-30-in-next-few-months), bulk carriers ship (http://www.eworldship.com/html/2020/bulk_market_0408/158450.html), Oil Tankers (http://www.eworldship.com/html/2020/ship_market_observation_0415/158673.html) and Other 19 ship class (http://www.msivt.com/news/archive/2020).

Residential and commercial buildings

The calculation of emissions was performed in three steps: 1) Calculation of population-weighted heating degree days for each country and for each day based on the ERA5 reanalysis of 2-meters air temperature, 2) Using the EDGAR estimates of 2018 residential emissions as the baseline. For each country, the residential emissions were split into two parts, i.e., cooking emissions and heating emissions, according to the EDGAR guidelines. The emissions from cooking were assumed to remain stable, while the emissions from heating were assumed to depend on and vary by the heating demand. 3) Based on the change of population-weighted heating degree days in each country, we scaled the EDGAR 2018 residential emissions to 2019 and 2020. Since the index of heating degree days are daily values, we can get daily emissions update for the residential sources globally. Note that the effect of increased time spent in households on residential buildings and decreased time in commercial and public buildings was not accounted for, since we did not have fuel consumption data for urban areas and building types. Our estimates of residential emissions changes are consistent with those obtained from the

City of Paris, based on individual electricity use (https://data.enedis.fr/) and population surveys (Y. Françoise pers. comm.).

Disaggregation of the subset of data available on a monthly basis into daily variations

For power sector, given the daily statistics of China is not available, we use the daily coal consumption of six main power company to re-allocate the total amount of monthly emissions from power sector to get the daily emissions of power sector in China. For the emissions from power sector in rest of world, we use the average growth rates of emissions from power sector in the quarter of 2020 of India, US, Europe (EU27 & UK), Russia, Japan and Brazil to estimate the growth rate of power emissions in the rest of world. For industrial sector, the statistical data are often lack of real-time and dynamic tracking updates, so we assume the industrial emissions have dropped -5% in Europe (EU27 & UK) and -3% in Japan and Russia in March. In addition, we use the daily electricity generation on national level to disaggregate the monthly industrial emissions into daily industrial emissions. For transport sector, because Google Mobility Reports only publish detailed mobility trends since February 15th, 2020, we assume the emissions are equal to the baseline value in all countries (except for China) before February 14th, 2020. In China, due to the lack of Baidu Migration Scale Index before January 11th, 2020, we use the average value of migration index between January 12th, 2019 and January 20th, 2019, to fill the data gap between January 1st 2019 to January 11th, 2019. We will keep updating our estimates based on fuller and more reliable data sources.

Uncertainty estimates

Uncertainty of using proxy data to assess changes during 2020 is within the uncertainty of the statistical data usually used to assess monthly emissions. Previous estimates suggested an uncertainty of $\pm 20\%(1\sigma)$ for fossil fuel CO2 emission in emerging economies like China and $\pm 5\%$ for the global average[31-33].. As a conservative uncertainty of using monthly, weekly or hourly proxy statistics of activity data (power generation, industrial output, road traffic) we assumed the same emission uncertainty when using these proxy data than when using monthly statistics in China to assess emissions[20]. This is a conservative estimation given that monthly statistics from China have a large uncertainty among those from other large emitters. Uncertainty from monthly statistics was derived from 10000 Monte Carlo simulations to estimate a 68% confidence interval (1-sigma) for China as in ref. [20]. We calculated the 68% prediction interval of linear regression models between emissions estimated from monthly statistics and official emissions obtained from annual statistics at the end of each year, to deduce the one-sigma uncertainty involved when using monthly data to represent the whole year's change (SI Figure S66). The squared correlation coefficients are within the range of 0.88 (e.g., coal production) and 0.98 (e.g., energy import and export data), which represent that only using the monthly data can explain 88% to 98% of the whole year's variation[20], while the remaining variation not covered yet reflect the uncertainty caused by the frequent revisions of China's statistical data after they are first published.

Satellite observation and data sources:

To validate the response of the atmosphere, including CO_2 concentration and air quality, to the decreased fossil fuel burning and transportation, we collected NO_2, aerosol optical depth (AOD) and column-averaged dry air mole fraction of CO_2 (XCO_2) data from satellites (NO_2 from OMI, AOD from MODIS and XCO_2 from GOSAT) and surface daily average nitrogen dioxide (NO_2, μg/m^3), carbon monoxide (CO, μg/m^3) from 1600 air quality monitoring sites (China and US, SI Figure S7) in to investigate the impact of COVID-19 on air quality and atmospheric CO_2.

Surface air quality data in China was collected from the daily report by Ministry of Ecology and Environment of China (http://www.mee.gov.cn/). Measurements of daily average nitrogen dioxide (NO2, μg/m3), carbon monoxide (CO, μg/m3), and particulate matter smaller than 2.5 μm (PM2.5, μg/m3) from 1580 sites used to estimate pollution changes between the first quarters of 2019 and 2020. Surface air quality data in U.S. is downloaded from the Air Quality System (AQS) operated by the U.S. Environmental Protection Agency (https://www.epa.gov/aqs). Measurements of daily maximum 1-hour NO2 (ppb), daily maximum 8-hour CO (ppm), and daily average PM2.5 (μg/m3) from 983 sites are used. For March 2020, data availability is limited in U.S. with 20 sites for NO2, 31 for CO, and 309 for PM2.5. Sites with missing data for NO2/CO (PM2.5) at over 20 (5) days in any months will be excluded.

We obtained monthly NO_2 data from the Ozone Monitoring Instrument (OMI) provided by Tropospheric Emission Monitoring Internet Service (TEMIS), which has with a spatial resolution of 0.125° x 0.125° and a temporal coverage from October 2004 to March 2020. We only included the data from January 2013 to March 2020 in the work (SI Figure S8). For AOD, we chose daily Level 2 MOD 04 data from MODIS[34] and then calculated the monthly averaged AOD f from January 2013 to March 2020. Only "good" and "very good" data (in AOD_550_Dark_Target_Deep_Blue_Combined_QA_Flag 2 and 3) were kept in the calculation. At last, we calculated the monthly XCO_2 data with a resolution of 2.5° x 2.5° from the Greenhouse Gases Observing Satellite "IBUKI" (GOSAT). Because of the delay in the data processing at National Institute for Environmental Studies (NIES), we used a bias-uncorrected version V02.81 for the period of January 2013 to March 2020. With the consideration of the focus on an abnormal event due to COVID-19, the bias-uncorrected data is proper for this study.

All of the monthly averaged data were re-gridded to 1° x 1°. We focused on four emitting regions, China, USA, EU4 (UK, France, Germany, and Italy), and Indian, and then calculated the country level monthly averaged NO_2, AOD, and XCO_2 values.

Surface air pollution in China was significantly reduced during the epidemic period (SI Figure 7). A deep reduction of NO2 by 31.7% was observed on January 24th 2020, one day after the lockdown for many provinces (Si Figure S7b). The reduction rates were 13.7% for PM2.5 and 16.5% for CO on the same day. A clear rebound (U shape) could be found for all pollution after the spring festival (February 5th) in 2019. However, such recovery was missing in 2020 due to the lockdown, leading to a decreasing trend all through the first quarter. On average, pollution concentrations decreased by 23.0% for NO2, 15.4% for PM2.5, and 12.5% for CO during January-March 2020 relative to the same period in 2019.

Pollution level in U.S. was also reduced by the epidemic but with smaller magnitude compared to that in China. Surface PM2.5 decreased in all first three months in 2020 relative to 2019 with the largest reduction of 20.6% in March. NO2 also exhibited large reductions of 9.0% on March 2020 compared to 2019, however, such reduction seemed affected by the limited site numbers (only 20). For example, one site in Salt Lake, Utah reported >200 ppb (normally <40) NO2 during March 20-23, 2020. Such episodes were likely caused by fires but weakened the reduction rate of NO2 after Middle March (SI Figure 7e).

Changes of CO were also limited in U.S., with opposite signs in January and March. Such tendencies could also be biased due to the limited site numbers (only 31).

The observed tropospheric nitrogen dioxide (NO2) column concentration data from satellite observation[35] and surface air quality data from ground monitoring networks have exhibited a decrease (SI Table S9) consistent with reduction of fossil carbon fuels emissions.

In China, January, February, and March 2020 decreased by -32.27%, -34.22%, -4.53% respectively compared to 2019. Overall, NO2 decreased over China by -23.67% in the first quarter of 2020 compared to 2019. In the US, the decrease of NO_2 first started in Feb and continued to decrease at least until March 2020. Compared to the same period of the year in 2019, NO_2 over the US decreased by -23.08% and -14.32% in February and March 2020, respectively (SI Table S9). For the UK, France, Germany, and Italy, we observe similar NO_2 decreases than over the USA India had weaker decline in NO_2 than other regions.

The decline rate of NO_2 (-25.73%) based on atmospheric observations can be used to check the consistency of the decrease of NO_2 emission from the inventory, and given the NO2 is mainly contributed by fossil fuel combustion with life time short than one day, the temporal change of NO2 emission can could verify the decrease of the fossil fuel combustion and the associated CO_2 emissions. For China where the most significant decrease of tropospheric NO_2 column concentration observed, the inventory-based estimates[36,37] of power generation (-6.8%), transportation (-37.2%) and industry(-8.1%) are adopted with result of weight mean -23.94% % NO2 emission in first quarter of 2020 when comparing with 2019. These three sectors together account for 96% of China's total NO2 emissions. The -23.42% decline of the NO_2 emissions from our bottom-up inventory is consistent with the satellite observed -26% decrease of column NO_2, and with the -23% decrease of near surface concentrations at the 1680 ground-based stations. For US, the inventory-based estimates of power generation (-4.9%), transportation (-2.7%) and industry(-2.2%) are adopted with result of -2.57% NO2 emission in first quarter of 2020 when comparing with 2019, slightly smaller than -4.76% tropospheric NO_2 column concentration, but difference with the site observation data (-8.98% in March and +0.34%for first quarter), which may be affected by site numbers (only 20 sites in US). We calculated 1° x 1° monthly mean of NO2, AOD, and XCO_2 from OMI, MODIS, and GOSAT, respectively (SI Table S9).

For satellite observations, the overall uncertainty of tropospheric NO2 columns monthly mean is 10%[38]. The uncertainty of AOD is approximately $0.03+0.20\tau_M$, where τ_M is AOD at 550 nm[39]. In other words, the uncertainties in percentage in low AOD regions (US and EU4) is higher in high AOD regions (China and India). The standard deviations of XCO_2 monthly mean over land are about 0.5-1.5 ppm[40]. Here we conservatively considered uncertainty of monthly XCO_2 as 1.5 ppm. To estimate the uncertainty of changes of 2020 compared to 2019 from January to March, we input above uncertainties of monthly means and run Monte Carlo simulations of 10000 trials to calculate the 68% confidence intervals (i.e., one sigma range) which are shown in Table 1.

Data Availability Statement

All data generated or analyzed during this study are included in this article (and its Data descriptor paper and supplementary information files).

Code Availability Statement

The code generated during and/or analyzed during the current study are available from the corresponding author on reasonable request.

Declaration

Authors declare no competing interests.

Acknowledgements

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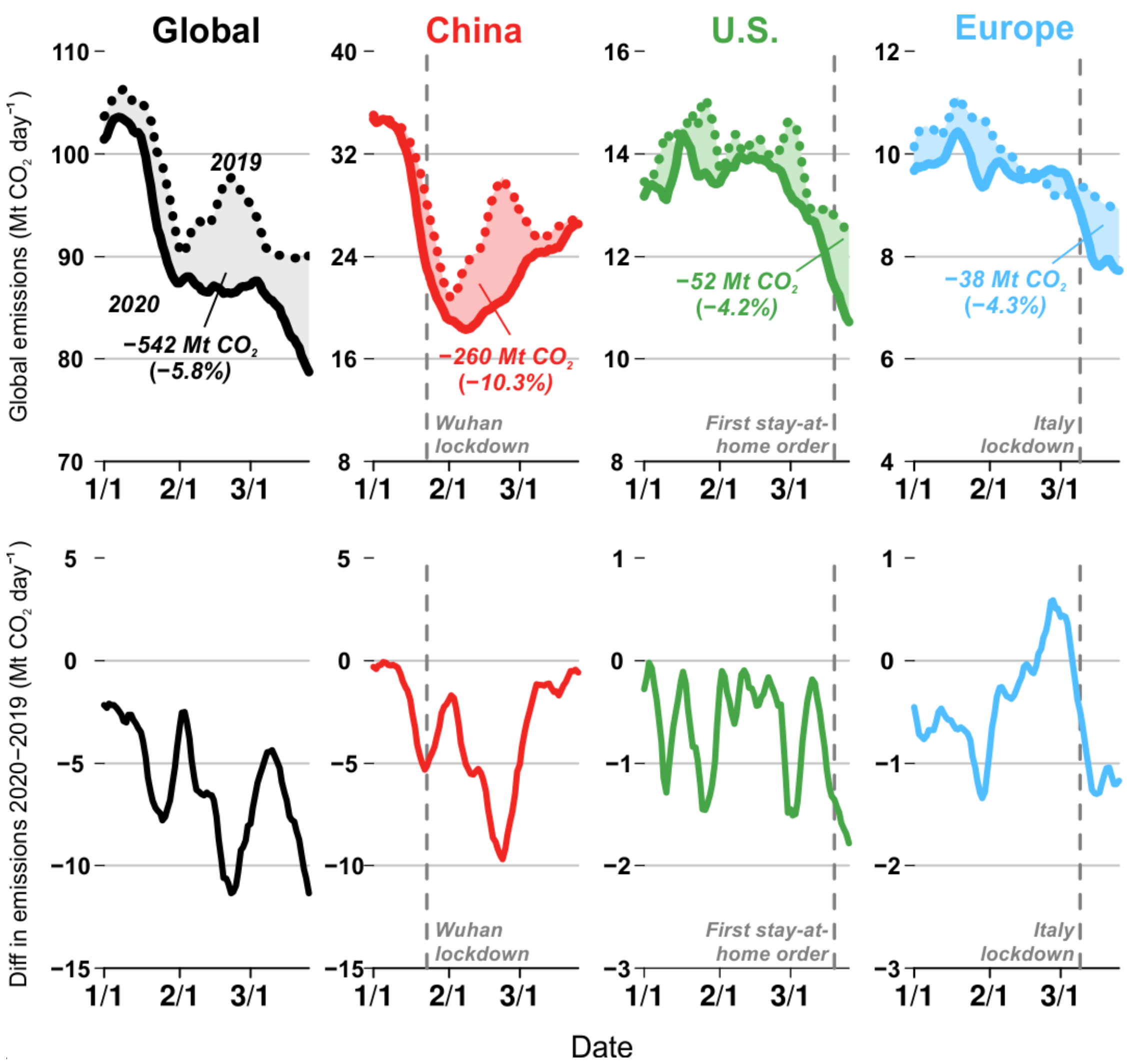
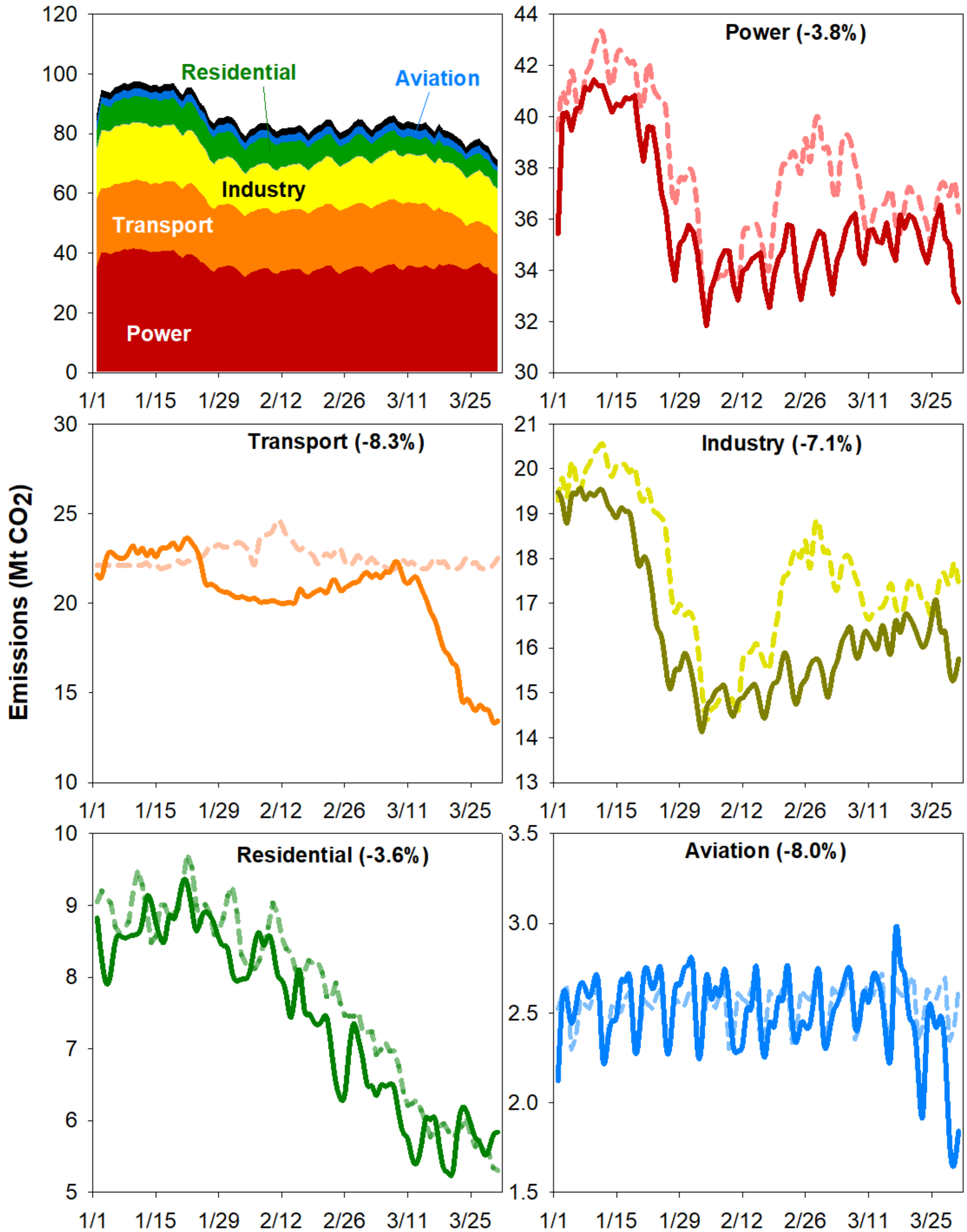
Supplementary Information

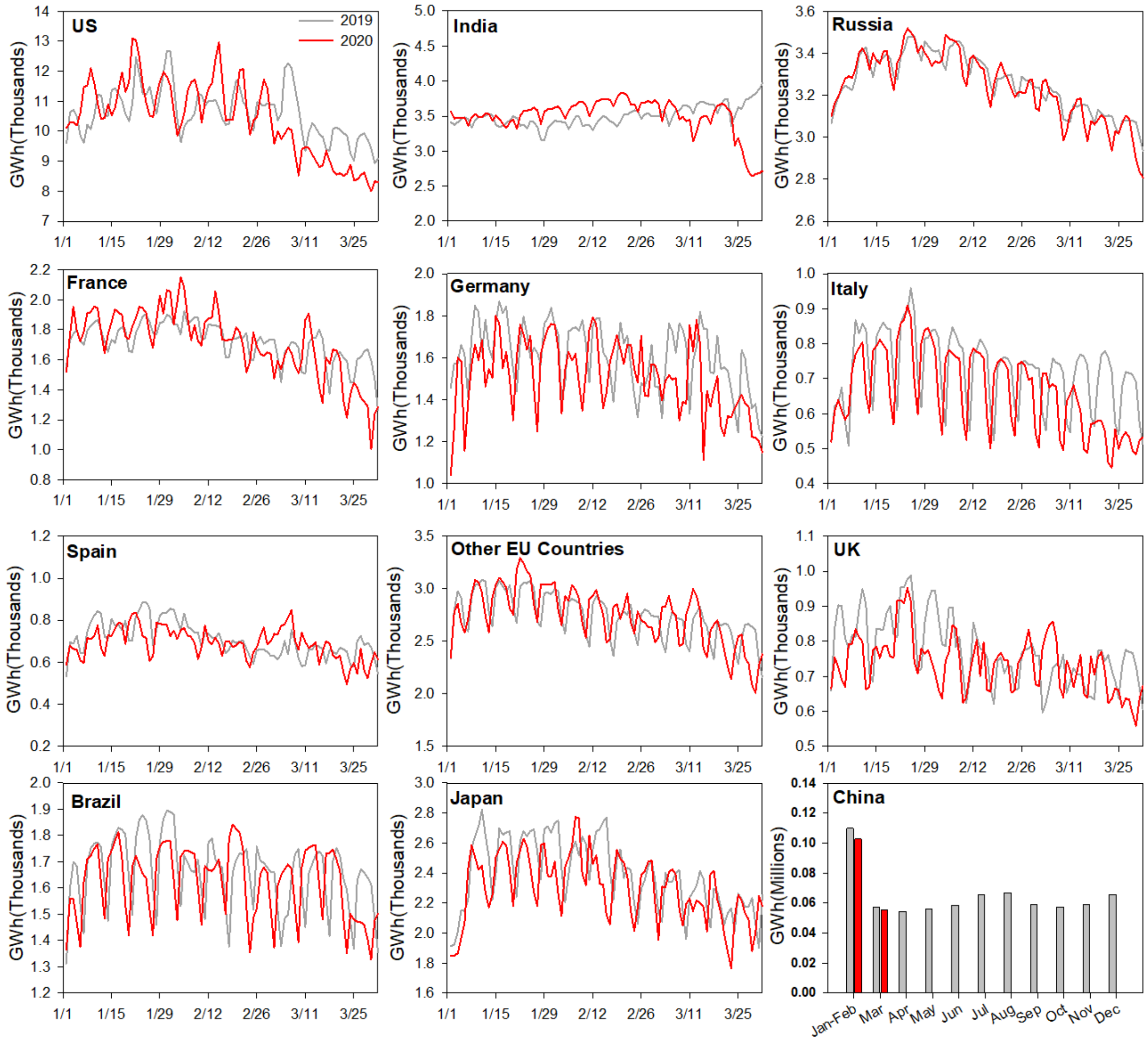


SI Figure S1. (top) Monthly CO_2 emissions in the first quarter of 2019 (dotted line) and 2020 for the world, China, US and Europe (EU27+UK). (bottom)

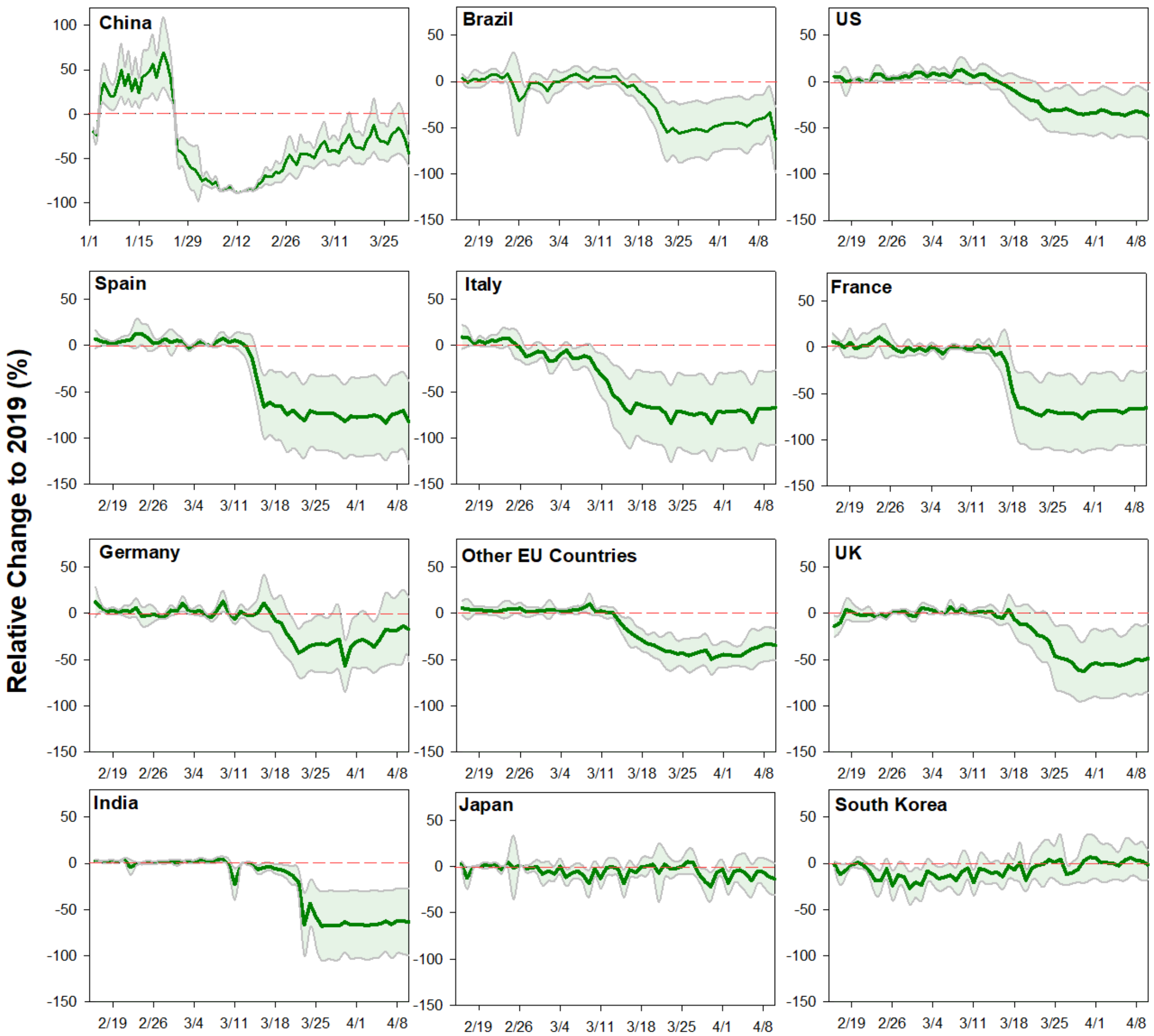
daily emission difference between 2020 minus 2019.



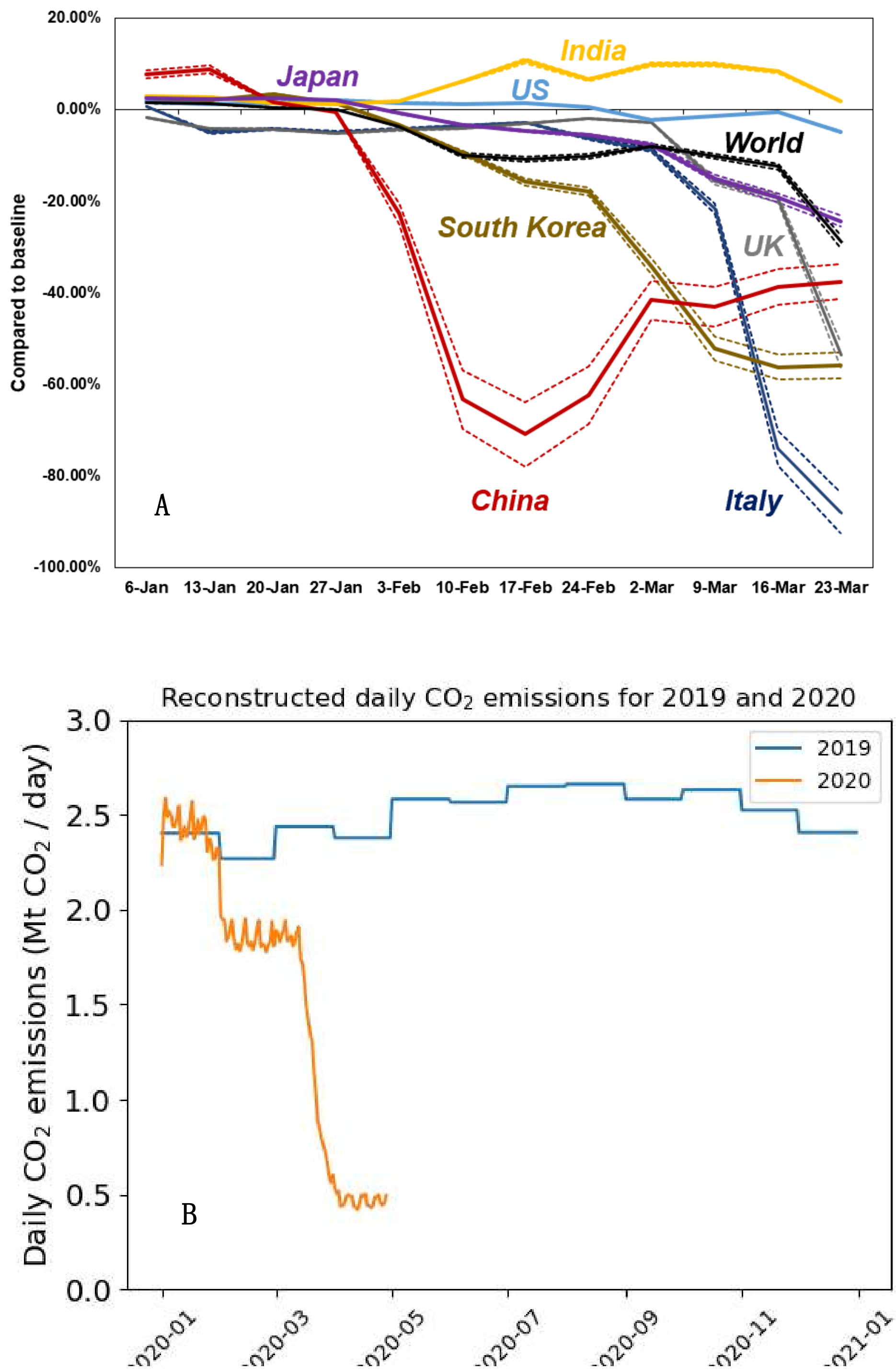
SI Figure S2 Daily global CO2 emission decline in the first quarter of 2020 by sectors



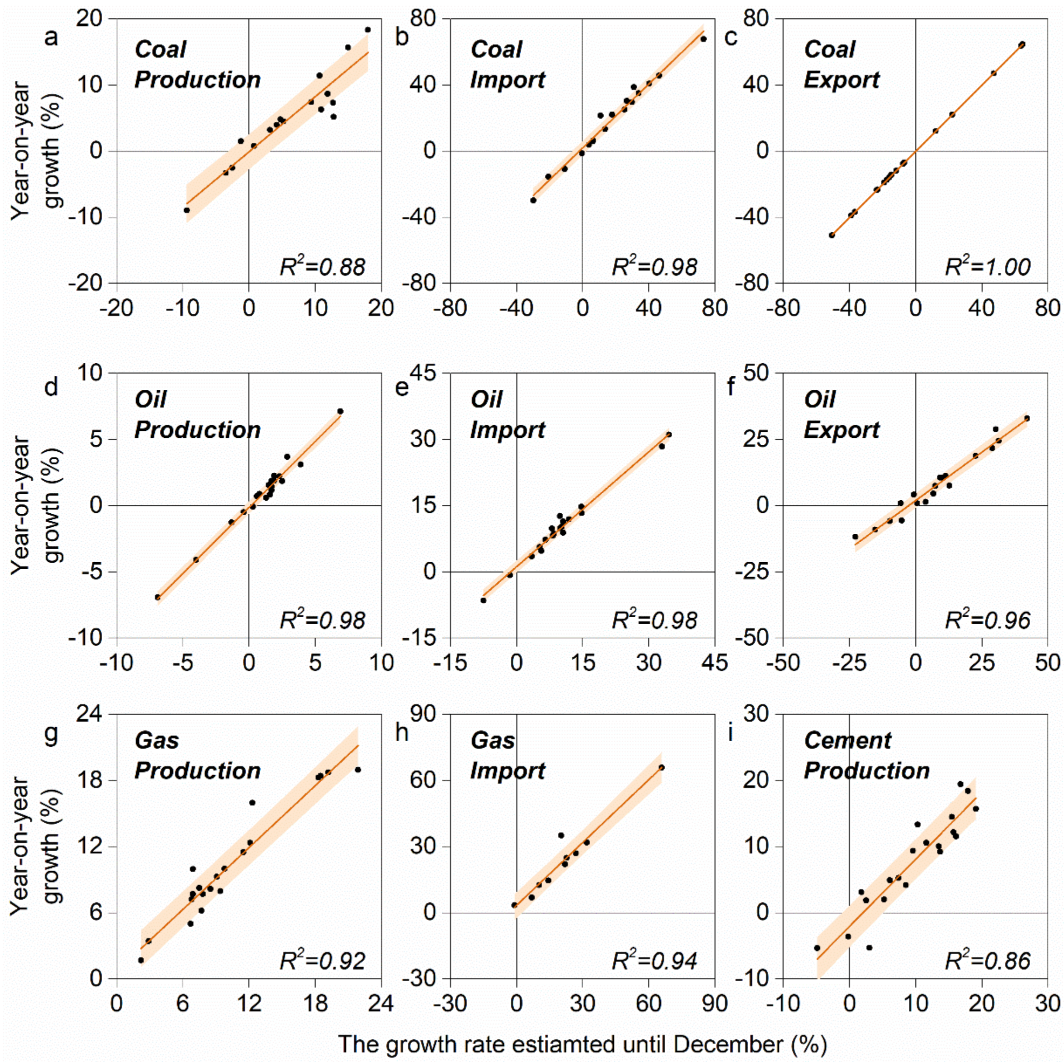
SI Figure S3 | Daily/monthly electricity generation in 2020 in US, India, Russia, France, Germany, Italy, Spain, other European countries (Austria, Belgium, Bulgaria, Czech Republic, Denmark, Estonia, Finland, Greece, Hungary, Latvia, Lithuania, Netherlands, Poland, Portugal, Romania, Slovakia, Slovenia, and Sweden), UK, Brazil, Japan and China, after being corrected by daily temperature (See Methods).



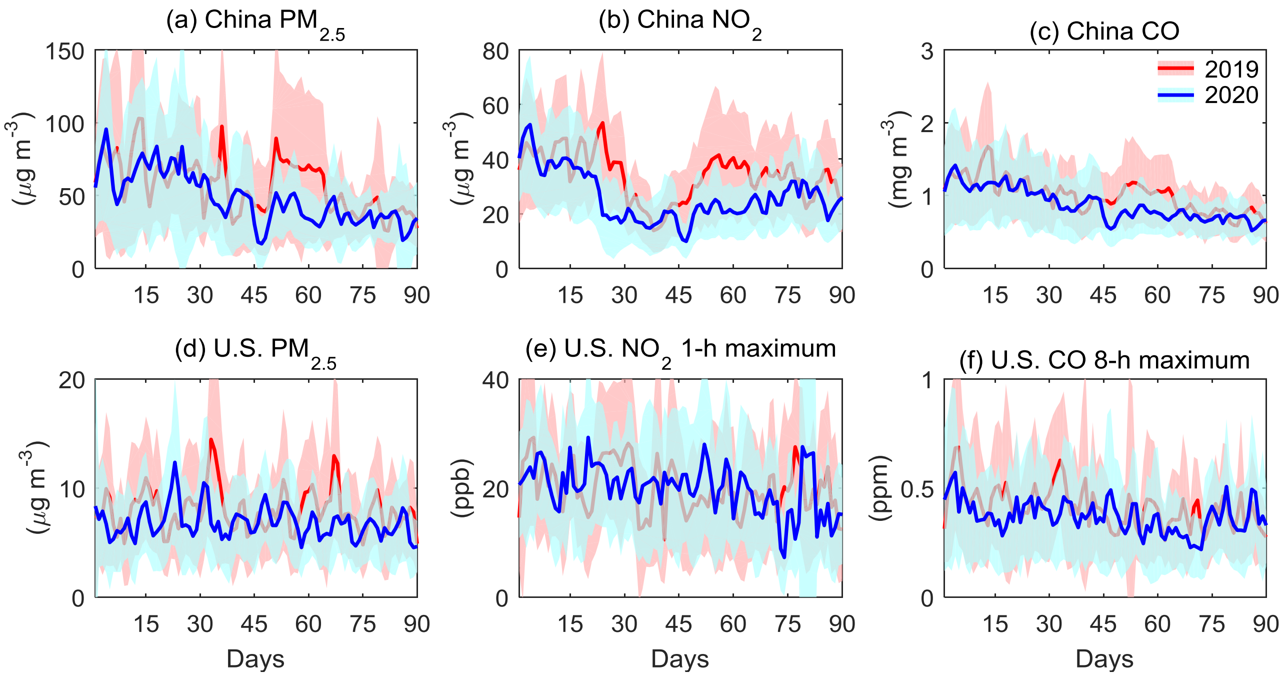
SI Figure S4 | Monthly emission changes in transport sector in February, March and the first quarter of 2020. (See SI Table 3)



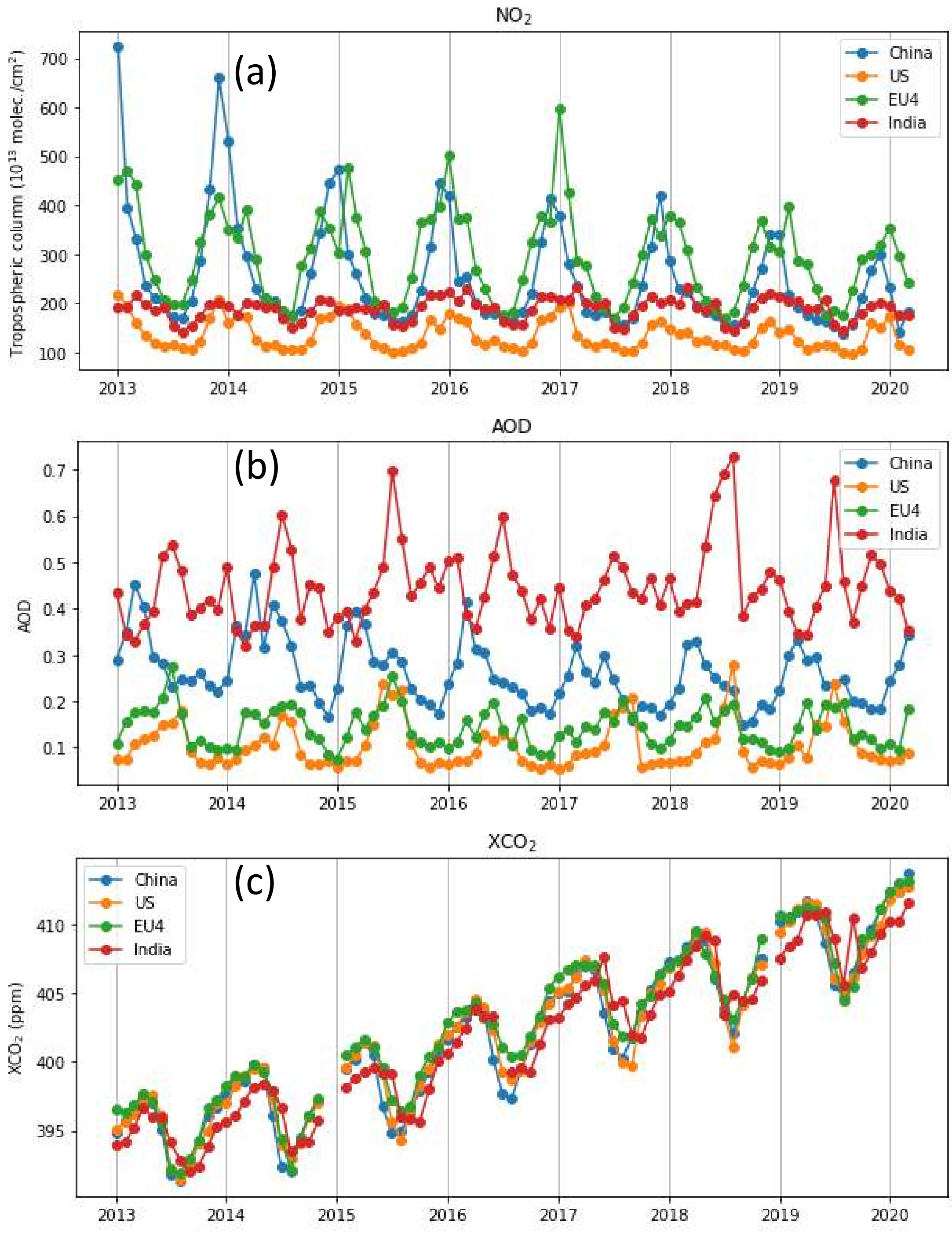
SI Figure S5. Change in numbers of the flights (A).Estimated daily CO2 emissions (Mt CO2/day) from all commercial flights for year 2020 (B). The estimated daily monthly-mean averages for 2019 used in the scaling are superposed for comparison.



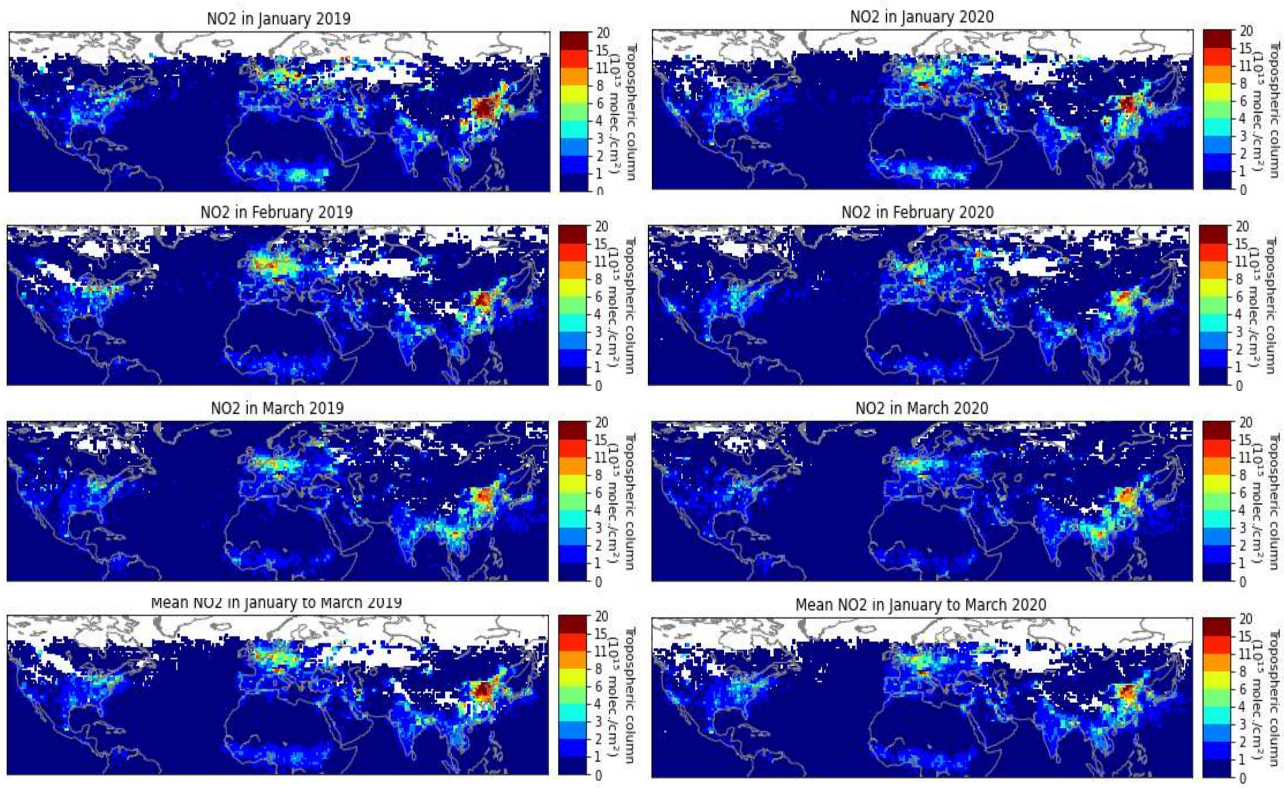
SI Figure S6. Correlation between the growth rates of monthly statistics with those from the whole year between 1990 and 2018. The x value is certain year's growth rate that calculated based on monthly statistics of the year, the y value is the growth rate for whole year. The consistence of the results shows robust about the calculation of one year's growth rate based one the monthly statistics.



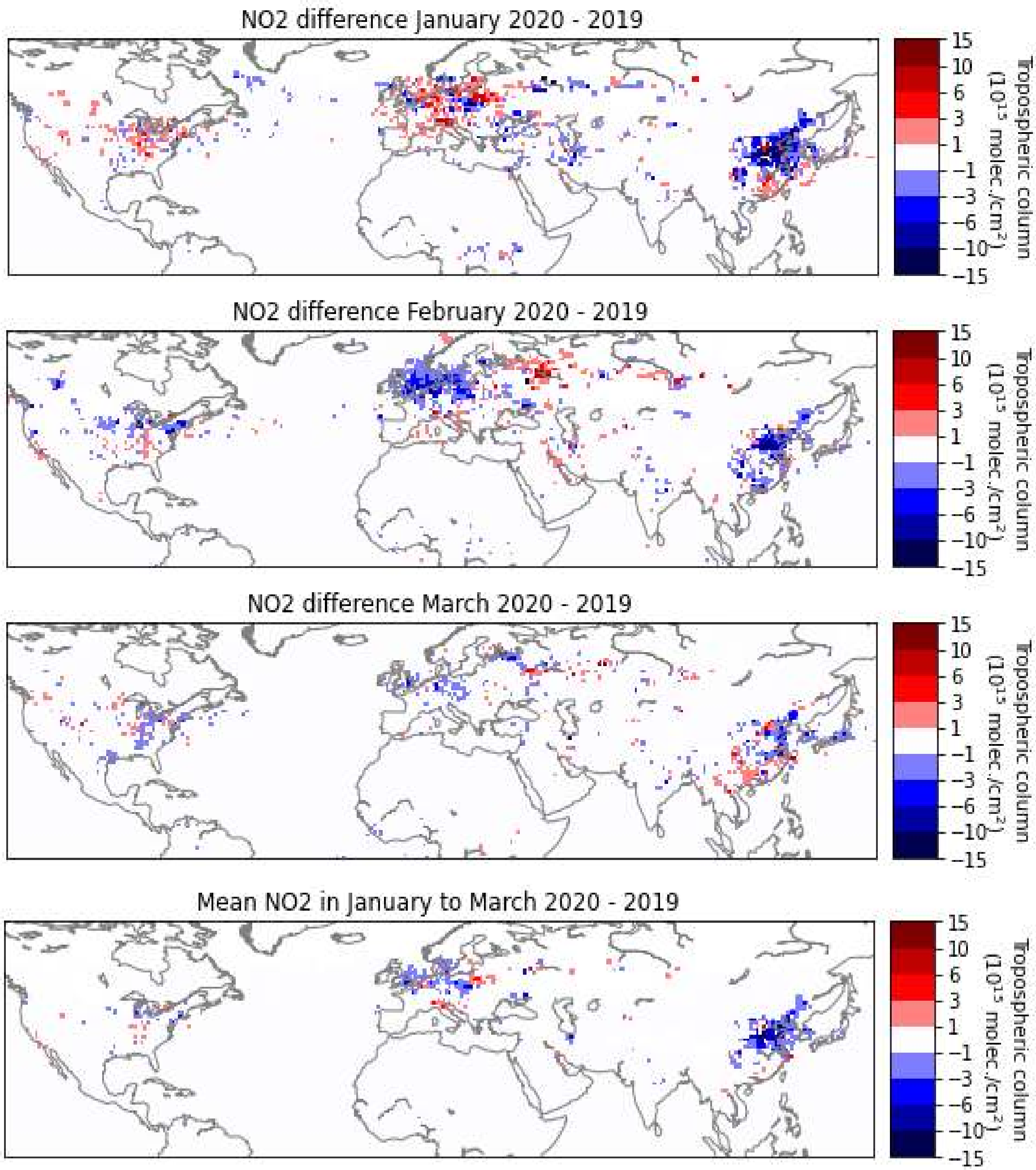
SI Figure S7. Daily variations of surface (a, d) $PM_{2.5}$, (b, d) NO_2, (c, f) CO concentrations from (a-c) China and (d-f) U.S. during the first quarters of 2019 and 2020. The bold lines are the mean values from all quality-controlled sites, with shadings indicating one standard deviation. The data on February 29th 2020 are removed from the plot.



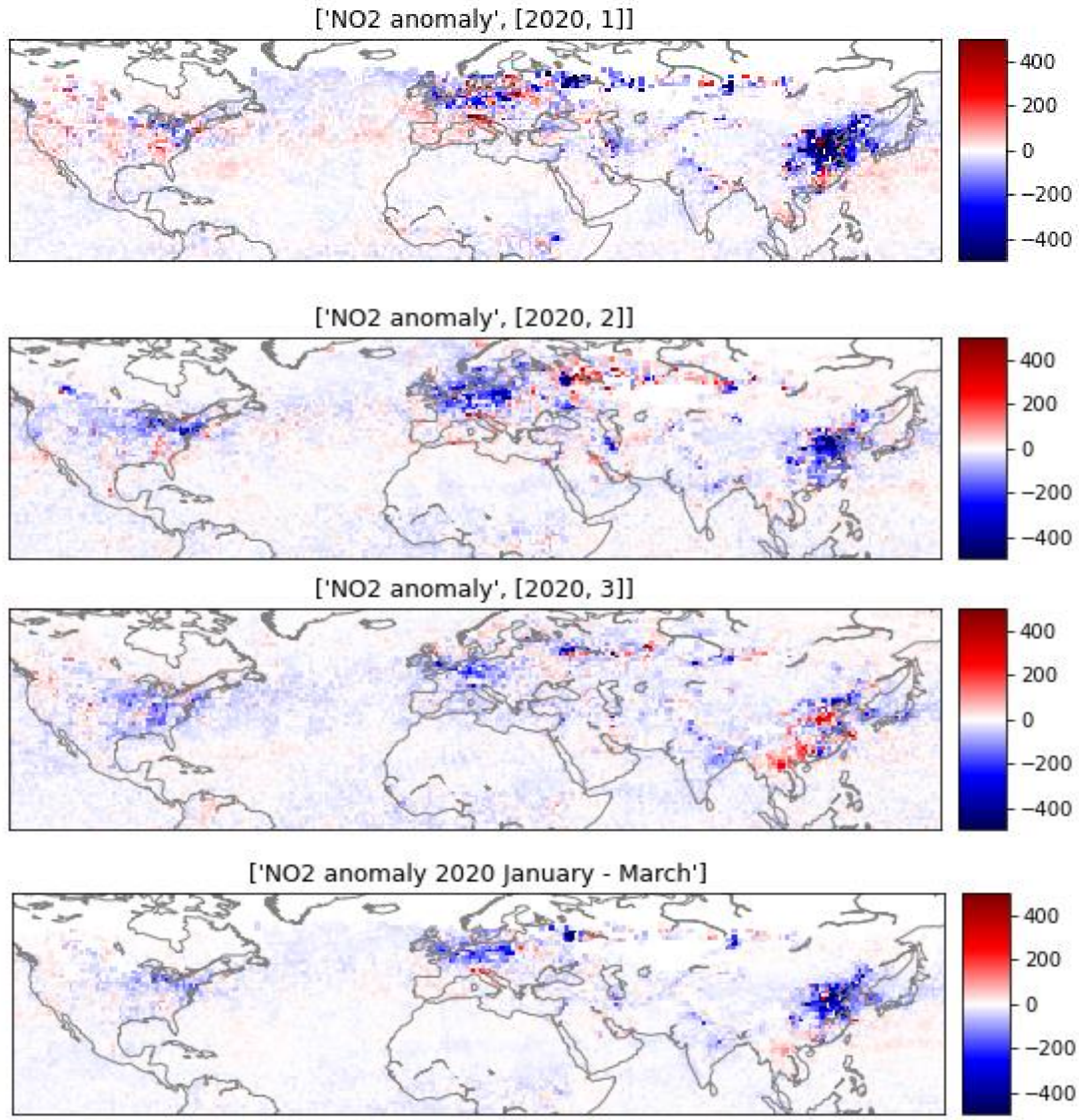
SI Figure S8. The monthly series of a) NO2, b) AOD and c) XCO2 over China, US, EU4(UK, Germany, Italy and France), and India



SI Figure S9 Tropospheric column NO2 Observation in the first quarter of 2020

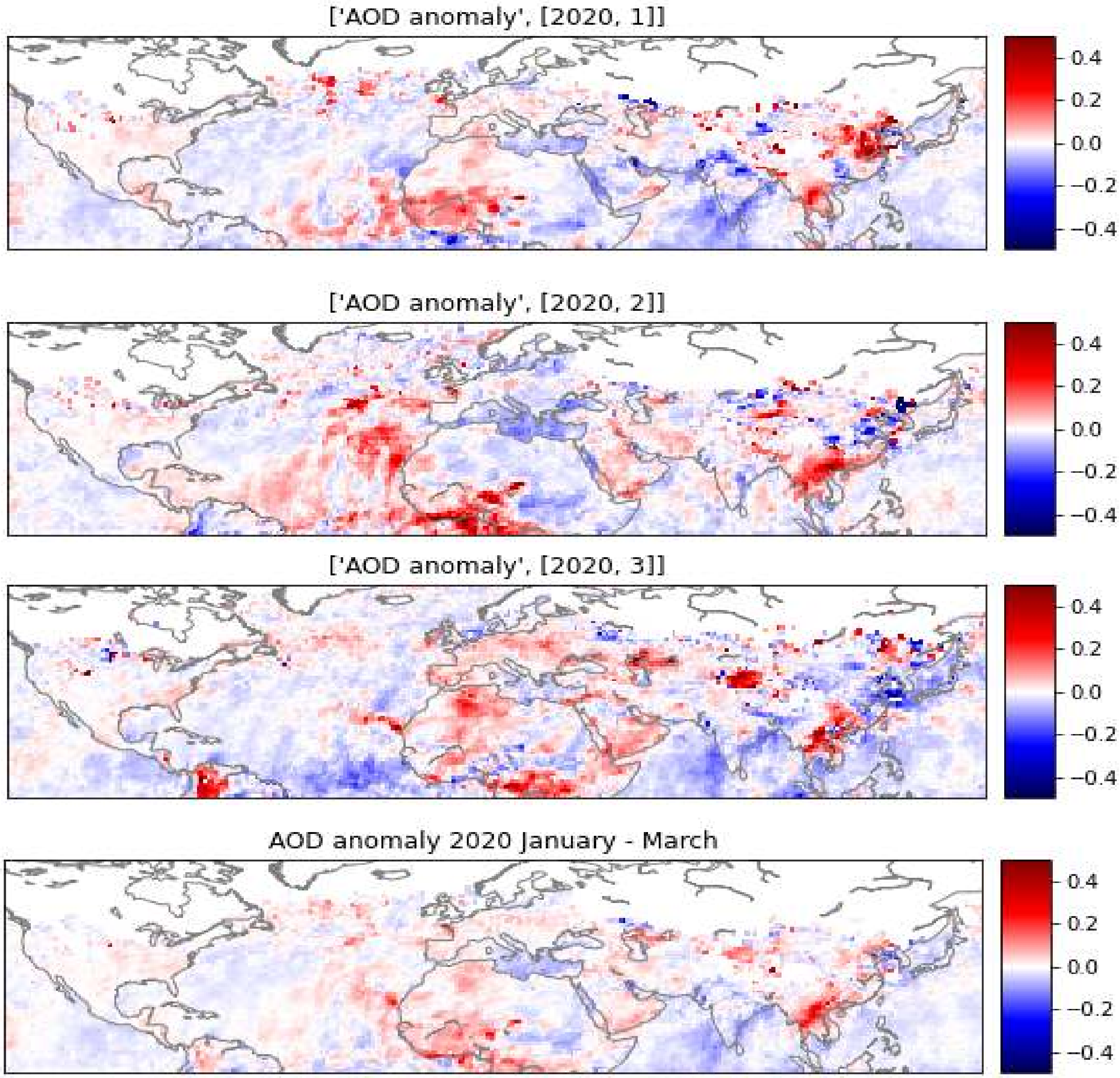


SI Figure S10 | Tropospheric column NO_2 Observation in the first quarter of 2020



SI Figure S11. Anomaly of NO2 from OMI in the first quarter of 2020

The anomaly maps conducted by apply the same algorithm on every grid point. The anomaly defined as the deseasonalized value. For NO2 (Figure S11), the anomaly along the eastern coast of China was negative in January and February 2020, then partially become positive. About half of the anomalies over U.S. and Europe were positive in January 2020, then most areas over U.S. and Europe became negative, which also matches the COVID-19 epidemic delays compared to China.



SI Figure S12 Anomaly of AOD from MODIS in the first quarter of 2020

The anomaly maps conducted by apply the same algorithm on every grid point. The anomaly defined as the deseasonalized value. For AOD (Figure S12), the negative anomaly area along the eastern coast of China expanded from January to March 2020. For US and Europe, AOD anomalies on land did not change too much. The shutdown of COVID-19 may not affect AOD over them since their AOD was always Low.

SI Table S1 Mapping table of sectors between this study and EDGAR[9].

This Study	EDGAR
Power	Electricity and heat production
Industry (from direct fuel combustion)	Manufacturing industries and construction
	Other energy industries
Ground Transport	Road transportation
	Rail transportation
	Inland navigation
	Other transportation
Residential	Residential and other sectors

SI Table S2. Sectoral changes in the first quarter in 2020 comparing to the same periods in 2019 by countries or regions.

Emission Decline ($MtCO_2$, 2020Q1)	Power	Transport	Industrial (with Process)	Residential	Sum	Growth Rates (%)
China	-76.2	-81.7	-90.2	-11.4	-259.5	-10.3%
India	3.0	-4.8	-15.5	7.0	-10.4	-1.6%
US	-21.7	-6.5	-4.9	-19.1	-52.3	-4.2%
Europe (EU27 & UK)	-8.5	-13.8	-6.4	-9.2	-38.0	-4.3%
Russia	-4.5	0.0	0.4	-8.5	-12.6	-3.0%
Japan	-4.0	-0.4	-6.1	-2.8	-13.2	-4.3%
Brazil	-0.2	-2.8	-1.3	0.0	-4.4	-4.1%
Row	-19.6	-25.6	-33.8	-3.7	-82.7	-3.3%
World	-131.6	-135.7	-157.9	-47.8	-473.0	-5.5%
Growth Rates (%)	-3.8%	-8.3%	-7.1%	-3.6%	-5.5%	
International aviation					-33.4	-8.0%
International shipping					-35.5	-13.3%
Global					-541.9	-5.8%

SI Table S3. Monthly changes in power sector in 2020 comparing to the same periods in 2019 by countries or regions.

Countries/Regions	**Jan**	**Feb**	**Mar**	**Jan-Mar**
China			-4.6%	-6.8%
India	2.7%	10.4%	-8.7%	1.0%
United States	-6.8%	-1.0%	-6.7%	-4.9%
Europe (EU27 & UK)	-5.4%	1.0%	-4.1%	-3.0%
Russia	-3.4%	0.5%	-2.9%	-2.0%
Japan	-5.4%	-0.1%	-2.1%	-2.7%
Brazil	-3.9%	2.2%	-1.3%	-1.1%
European Countries				
Austria	-14.5%	7.7%	-2.2%	-3.7%
Belgium	1.4%	8.2%	-3.6%	1.8%
Bulgaria	-14.1%	-9.0%	-10.6%	-11.3%
Czech Republic	-5.7%	-5.4%	-5.3%	-5.5%
Denmark	2.3%	16.8%	-12.7%	1.5%
Estonia	-62.4%	-48.3%	-43.7%	-53.3%
Finland	-10.1%	0.3%	2.9%	-2.6%
France	-2.0%	1.7%	-4.6%	-1.7%
Germany	-8.6%	0.3%	-8.2%	-5.7%
Greece	-15.9%	-5.1%	-9.0%	-10.7%
Hungary	-4.7%	18.4%	21.3%	9.8%
Italy	-5.7%	-2.5%	-14.5%	-7.6%
Latvia	5.1%	27.7%	-1.6%	8.6%
Lithuania	4.2%	33.1%	-0.3%	11.5%
Netherlands	67.1%	6.9%	-15.1%	13.8%
Poland	-7.2%	1.3%	-5.6%	-4.0%
Portugal	15.8%	15.8%	17.7%	16.4%
Romania	-0.8%	-5.5%	-3.0%	-3.1%
Slovakia	-2.8%	8.3%	-3.1%	0.5%
Slovenia	3.7%	-10.9%	0.7%	-2.3%
Spain	-7.2%	-0.8%	2.2%	-2.2%
Swede	3.5%	5.6%	6.6%	5.2%
United Kingdom	-8.9%	0.0%	-0.9%	-3.6%

SI Table S4. Monthly mobility changes in 2020 comparing to the same periods in 2019 by countries or regions.

Countries/Regions	Jan	Feb	Mar	Jan-Mar
China	7.4%	-75.1%	-34.2%	-36.2%
India	-	4.1%	-22.9%	-6.6%
United States	-	5.9%	-10.0%	-1.6%
Europe (EU27 & UK)	-	5.2%	-22.8%	-6.2%
Brazil	-	2.9%	-5.3%	-0.9%
Japan	-	3.2%	-20.0%	-5.9%
European Countries				
Austria	-	7.8%	-26.9%	-7.9%
Belgium	-	2.9%	-22.5%	-8.0%
Bulgaria	-	6.9%	-20.7%	-6.1%
Croatia	-	6.1%	-21.1%	-6.5%
Czechia	-	6.3%	-17.6%	-5.2%
Denmark	-	3.4%	-7.5%	-2.6%
Estonia	-	4.3%	-9.6%	-3.1%
Finland	-	4.4%	-8.3%	-2.6%
France	-	4.7%	-31.6%	-10.5%
Germany	-	4.6%	-10.9%	-3.4%
Greece	-	6.2%	-24.0%	-7.5%
Hungary	-	7.8%	-12.7%	-3.1%
Ireland	-	2.7%	-16.6%	-6.0%
Italy	-	4.3%	-48.3%	-16.4%
Latvia	-	4.5%	-5.5%	-1.6%
Lithuania	-	4.9%	-11.9%	-3.7%
Luxembourg	-	2.9%	-25.5%	-9.0%
Malta	-	9.6%	-21.4%	-5.5%
Netherlands	-	3.1%	-11.7%	-4.2%
Poland	-	5.1%	-19.9%	-6.4%
Portugal	-	7.1%	-28.6%	-8.8%
Romania	-	5.8%	-20.3%	-6.3%
Slovakia	-	6.8%	-23.9%	-7.2%
Slovenia	-	5.9%	-27.3%	-8.7%
Spain	-	6.6%	-37.6%	-12.0%
Sweden	-	4.0%	-3.1%	-0.9%
United Kingdom	-	2.5%	-13.8%	-5.1%

SI Table S5. Monthly emission changes based on TomTom congestion level by countries or regions.

Countries/Regions	Jan	Feb	Mar	Jan-Mar
China	-21%	-55%	-27%	-34%
India	1%	-4%	-27%	-10%
United States	9%	5%	-16%	-1%
Brazil	3%	-4%	-15%	-5%
Japan	-3%	-3%	-7%	-5%
European Countries				
Austria	3%	6%	-10%	-1%
Belgium	7%	7%	-9%	1%
Bulgaria	4%	0%	-9%	-2%
Czechia	4%	2%	-9%	-1%
Estonia	8%	8%	-6%	3%
Finland	-6%	-7%	-12%	-8%
France	9%	0%	-19%	-4%
Germany	4%	4%	-8%	0%
Hungary	3%	1%	-8%	-1%
Ireland	4%	3%	-11%	-2%
Italy	4%	1%	-23%	-6%
Latvia	2%	2%	-9%	-2%
Lithuania	6%	5%	-6%	2%
Luxembourg	7%	2%	-7%	1%
Netherlands	4%	3%	-10%	-1%
Poland	4%	2%	-8%	-1%
Portugal	9%	7%	-18%	-1%
Romania	-2%	3%	-12%	-4%
Slovakia	8%	5%	-7%	2%
Slovenia	23%	7%	-11%	6%
Spain	11%	8%	-23%	-2%
Sweden	0%	-3%	-11%	-5%
United Kingdom	6%	4%	-9%	-1%

SI Table S6. Growth rates of industrial emissions from direct fuel combustion comparing to the same periods of last year in 2020.

Countries/Regions	Jan	Feb	Mar	Jan-Mar
China			-6.9%	-8.1%
India	-0.4%	3.9%	-22.7%	-7.0%
U.S.	-1.2%	0.1%	-5.5%	-2.2%
EU27 & UK	-1.6%	-1.6%	-6.4%	-3.2%
Japan	-2.4%	-5.7%	-17.4%	-8.9%
Brazil	-0.9%	-0.5%	-5.8%	-2.4%
Russia	1.1%	3.3%	0.4%	1.6%

SI Table S7. Growth rates of crude steel production comparing to the same periods of last year in 2020.

Countries/Regions	Jan	Feb	Mar	Jan-Mar
China	1.4%	5.0%	-1.7%	1.4%
India	-3.1%	1.5%	-13.9%	-5.3%
U.S.	1.8%	1.6%	-6.0%	-1.0%
EU27 & UK	-7.6%	-1.2%	-20.9%	-10.3%
World	-0.6%	3.3%	-6.0%	-1.3%

SI Table S8. Growth rates of industrial emissions from direct fuel combustion by different industries in China and India comparing to the same periods of last year in 2020.

Changes in China industrial Sector	Jan	Feb	Mar	Jan-Mar
Steel industry	1.4%	5.0%	-1.7%	1.4%
Cement industry			-18.3%	-23.9%
Chemical industry			0.1%	-4.2%
Other industry			-10.6%	-13.6%
Changes in India industrial Sector	**Jan**	**Feb**	**Mar**	**Jan-Mar**
Steel industry	-3.1%	1.5%	-13.9%	-5.3%
Cement industry	5.0%	8.6%	-40.0%	-10.2%

SI Table S9. The observation of air quality and dry column CO_2 (XCO_2) (Full Data file attached separately)

		China	US	EU4	India
OMI NO2	**Jan**	-32.26% ± 12.03%	22.98% ± 16.02%	15.78% ± 15.24%	-8.96% ± 13.63%
	Feb	-34.22% ± 11.87%	-23.08% ± 12.63%	-25.12% ± 12.40%	-13.79% ± 13.36%
	Mar	-4.53% ± 13.77%	-14.32% ± 13.24%	-15.56% ± 13.22%	-13.37% ± 13.29%
	Jan-Mar	-25.73% ± 12.51%	-4.76% ± 13.75%	-9.71% ± 13.54%	-11.99% ± 13.47%
MODIS AOD	**Jan**	10.17% ± 49.22%	10.64% ± 95.67%	19.81% ± 77.76%	-5.46% ± 36.27%
	Feb	-7.88% ± 41.08%	-3.98% ± 82.64%	-1.95% ± 70.78%	7.29% ± 39.89%
	Mar	3.55% ± 41.88%	-15.65% ± 67.37%	29.42% ± 62.28%	1.84% ± 41.12%
	Jan-Mar	1.26% ± 44.04%	-5.08% ± 79.02%	17.51% ± 69.42%	0.81% ± 38.88%
GOSAT XCO2	**Jan**	0.53% ± 0.52%	0.60% ± 0.52%	0.42% ± 0.52%	0.65% ± 0.52%
	Feb	0.45% ± 0.51%	0.53% ± 0.52%	0.65% ± 0.52%	0.44% ± 0.51%
	Mar	0.67% ± 0.52%	0.37% ± 0.52%	0.51% ± 0.52%	0.66% ± 0.52%
	Jan-Mar	0.55% ± 0.52%	0.50% ± 0.52%	0.52% ± 0.51%	0.58% ± 0.52%
TROPOMI CO	**Jan**	2.67%±5.20%	4.94%±3.02%	2.37%±1.89%	-0.41%±3.37%
	Feb	0.47%±7.11%	2.97%±3.91%	1.08%±2.33%	3.23%±5.20%
	Mar	3.98%±6.77%	-1.84%±3.39%	-1.14%±3.10%	2.12%±3.45%
	Jan-Mar	2.38%±4.84%	1.85%±1.94%	0.72%±1.40%	1.66%±2.38%
Site NO2	**Jan**	-18.05%±23.90%	-3.80%±12.80%		
	Feb	-30.33%±21.78%	14.98%±68.82%		
	Mar	-23.03%±17.29%	-8.98%±44.17%		
	Jan-Mar	-23.00%±14.97%	0.34%±79.05%		
Site PM2.5	**Jan**	-2.67%±41.56%	-8.77%±49.43%		
	Feb	-26.71%±26.94%	-14.78%±59.12%		
	Mar	-21.80%±17.51%	-20.55%±39.30%		
	Jan-Mar	-15.39%±19.06%	-14.68%±40.49%		
Site CO	**Jan**	-5.89%±22.22%	-12.35%±23.12%		
	Feb	-19.60%±20.49%	-6.19%±45.39%		
	Mar	-14.24%±19.77%	4.94%±74.21%		
	Jan-Mar	-12.51%±15.41%	-5.11%±26.53%		
Inventory NO2	**Jan**		-0.99% (-1.36~-0.86%)		
	Feb		2.43% (2.11~3.33%)		
	Mar	-15.49% (-21.20~-13.46%)	-7.72% (-10.58~-6.72%)		
	Jan-Mar	-17.47% (-23.94~-15.20%)	-2.57% (-3.52~-2.24%)		