Carbon Monitor, near-real time daily datasets of global and regional CO_2 emissions from fossil fuel and cement production

Important notes

🆕 *20251008: We updated the baseline emissions by using data from UNFCCC national greenhouse gas inventories. Check details here.*

How to cite the data

[for Carbon Monitor]:

Deng, Z., Zhu, B., Davis, S.J. *et al*. **Global carbon emissions and decarbonization in 2024**. *Nat Rev Earth Environ* **6**, 231–233 (2025). https://doi.org/10.1038/s43017-025-00658-x

Liu, Z., Deng, Z., Davis, S.J. *et al*. **Global carbon emissions in 2023**. *Nat Rev Earth Environ* **5**, 253–254 (2024). https://doi.org/10.1038/s43017-024-00532-2

Liu, Z., Deng, Z., Davis, S. *et al*. **Monitoring global carbon emissions in 2022**. *Nat Rev Earth Environ* **4**, 205–206 (2023). https://doi.org/10.1038/s43017-023-00406-z

Liu, Z., Deng, Z., Zhu, B. *et al*. **Global patterns of daily CO_2 emissions reductions in the first year of COVID-19.** *Nat. Geosci.* (2022). https://doi.org/10.1038/s41561-022-00965-8

Davis, S.J., Liu, Z., Deng, Z. *et al*. **Emissions rebound from the COVID-19 pandemic**. *Nat. Clim. Chang*. **12**, 412–414 (2022). https://doi.org/10.1038/s41558-022-01332-6

Liu, Z., Deng, Z., Davis, S.J. *et al*. **Monitoring global carbon emissions in 2021**. *Nat Rev Earth Environ* **3**, 217–219 (2022). https://doi.org/10.1038/s43017-022-00285-w

Liu, Z., Ciais, P., Deng, Z. *et al.* **Near-real-time monitoring of global CO_2 emissions reveals the effects of the COVID-19 pandemic**. *Nat Commun* **11**, 5172 (2020). https://doi.org/10.1038/s41467-020-18922-7

Liu, Z., Ciais, P., Deng, Z. *et al*. **Carbon Monitor, a near-real-time daily dataset of global CO2 emission from fossil fuel and cement production**. *Sci Data* **7**, 392 (2020). https://doi.org/10.1038/s41597-020-00708-7

[*for Carbon Monitor-U.S.*]:

Hong, C., Ciais, P., Liu, Z., Boucher, O., Zhao, W., Gentine, P., Wang, Y., Deng, Z., and Davis, S.J.. **Near-real-time and state-level monitoring of U.S. CO_2 emissions**. *EarthArXiv* preprint: https://doi.org/10.31223/X5BS5B

[*for Carbon Monitor-EU*]:

Ke, P., Deng, Z., Zhu, B. et al. **Carbon Monitor Europe near-real-time daily CO2 emissions for 27 EU countries and the United Kingdom.** *Sci Data* **10**, 374 (2023). https://doi.org/10.1038/s41597-023-02284-y

[*for Carbon Monitor-Cities*]:

Huo, D., Huang, X., Dou, X. *et al*. **Carbon Monitor Cities near-real-time daily estimates of CO2 emissions from 1500 cities worldwide**. *Sci Data* **9**, 533 (2022). https://doi.org/10.1038/s41597-022-01657-z

Huo, D., Liu, K., Liu, J. *et al*. **Near-real-time daily estimates of fossil fuel CO2 emissions from major high-emission cities in China**. *Sci Data* **9**, 684 (2022). https://doi.org/10.1038/s41597-022-01796-3

[*for Carbon Monitor-Power*]:

Zhu, B., Deng, Z., Song, X. *et al*. **CarbonMonitor-Power near-real-time monitoring of global power generation on hourly to daily scales**. *Sci Data* **10**, 217 (2023). https://doi.org/10.1038/s41597-023-02094-2

The numbers in these manuscripts and publications may be slightly different (within 1%) from those of the web site due to minor updates. Note the web site does not show international shipping emissions, which are provided in the publications

Contributors

Zhu Liu[1*†], Philippe Ciais[2*†], Zhu Deng[1†], Steven J. Davis[3*], Bo Zheng[2], Yilong Wang[4], Xuanren Song[1], Duo Cui[1], Biqing Zhu[1], Xinyu Dou[1], Piyu Ke[1], Taochun Sun[1], Rui Guo[1], Olivier Boucher[5], François-Marie Bréon[2], Chenxi Lu[1], Runtao Guo[6], Eulalie Boucher[7], Frederic Chevallier[2], Katsumasa Tanaka[2,8], Chaopeng Hong[3]

[1] Department of Earth System Science, Tsinghua University, Beijing 100084, China.
[2] Laboratoire des Sciences du Climate et de l'Environnement LSCE, Institut Pierre Simon Laplace, CEA CNRS UVSQ UPSACLAY Orme de Merisiers 91191

Gif-sur-Yvette, France
[3] Department of Earth System Science, University of California, Irvine, 3232 Croul Hall, Irvine, CA 92697-3100, USA
[4] Key Laboratory of Land Surface Pattern and Simulation, Institute of Geographical Sciences and Natural Resources Research, Chinese Academy of Sciences, Beijing, China
[5] Institute Pierre-Simon Laplace, Sorbonne Université / CNRS, Paris, France
[6] School of Mathematical School, Tsinghua University, Beijing 100084, China
[7] Université Paris Dauphine, PSL, France
[8] Center for Global Environmental Research, National Institute for Environmental Studies, Tsukuba, Japan
[†] contributed equally

Fair use data policy

Carbon Monitor data are made freely available to the public and the scientific community in the belief that their wide dissemination will lead to greater understanding and new scientific insights. The availability of these data does not constitute publication of the data. The data providers rely on the ethics and integrity of the user to ensure that they receive fair credit for their work. If the data are obtained for potential use in a publication or presentation, we kindly ask you to inform us at the outset of the nature of this work. If the Carbon Monitor data are essential to the work, or if an important result or conclusion depends on the Carbon Monitor data, co-authorship may be appropriate. This should be discussed at an early stage in the work. Manuscripts using the Carbon Monitor data should be sent to for review before they are submitted for publication so we can ensure that the quality and limitations of the data are accurately represented. Contacts about the data: contact.carbonmonitor@gmail.com or zhuliu@tsinghua.edu.cn (for Asia and other regions), philippe.ciais@lsce.ipsl.fr (for Europe), sjdavis@uci.edu (for North America)

Disclaimer

Carbon Monitor data are made freely available to the public with the above fair use open data policy. We encourage users to cite the data by https://doi.org/10.1038/s41467-020-18922-7, https://doi.org/10.1038/s41597-023-02284-y or https://doi.org/10.31223/X5BS5B. Carbon Monitor is a living dataset subject to updates and the values are expected to change, as new data get included. In the process of updating our daily CO2 emission products, errors may be corrected, revisions may be made in the calculation methods, and new information may be used. Data files available for download and graphs are associated to a day of release. In case of questions regarding data and history previous releases, please contact us at contact.carbonmonitor@gmail.com. All information displayed and provided can be used at the own responsibility of users, and does not

engage any responsibility from research institutions supporting Carbon Monitor and partner institutions.

What is Carbon Monitor?

Carbon Monitor is a frequently-updated daily CO_2 emission dataset, to monitor the variations of CO_2 emissions from fossil fuel combustion and cement production since January 1st 2019 at national level with near-global coverage. Daily CO_2 emissions are estimated from a diverse range of activity data, including: hourly to daily electrical power generation data of 29 countries, monthly production data and production indices of industry processes of 62 countries/regions, daily mobility data and mobility indices of road transportation of 416 cities worldwide. Individual flight location data and monthly data were utilised for aviation and maritime transportation sectors estimates. In addition, monthly fuel consumption data that corrected for daily air temperature of 206 countries were used for estimating the emissions from commercial and residential buildings. Carbon Monitor data show the dynamic nature of CO_2 emissions through daily, weekly and seasonal variations as influenced by workdays and holidays, as well as the unfolding impacts of the COVID-19 pandemic. Carbon Monitor shows a 7.8% decline of CO_2 emission globally from Jan 1st to Apr 30th in 2020 when compared with the same period in 2019, and detects a re-growth of CO_2 emissions by late April mainly attributed to the recovery of economic activities in China and partial easing of lockdowns in other countries.

Background

The main cause of global climate change is the anthropogenic emission of CO_2 to the atmosphere from geological carbon reservoirs, namely fossil fuel burning and cement production. Dynamic information on those fossil CO_2 emissions is critical for understanding the human forcing of climate change. Further, the combustion of fossil fuels emits short-lived pollutants such as SO_2, NO_2 and CO which affect air quality and climate. Therefore, information on CO_2 emissions also allows a more accurate quantification od the emissions of those pollutants for air quality and climate studies[1,2]. Estimates of fossil CO_2 emissions[2-8] rely on activity data (e.g., the amount of fuel burnt or energy produced) and emission factors (See Methods)[9]. The sources of these data are mainly national energy statistics, and organizations such as CDIAC, BP, EDGAR, IEA and GCP also produce estimates for different groups of countries or for all countries[1,10-12]. Fossil CO_2 emissions are usually on an annual basis lagging the very year's emissions by at least one year.

The uncertainty associated with fossil CO_2 emissions is smaller for large emitters or the globe, than that of emissions from co-emitted pollutants for which uncertain technological

factors influence the ratio of emitted pollutants to CO_2 [13-15]. The uncertainty of global fossil CO_2 emissions varies between ±6% and ±10%[5,7,16,17] (±2σ), reflecting uncertain activity data and the emission factors. For activity data, the amount of fuel burnt is recorded by energy production and consumption statistics, hence uncertainties arise from errors and inconsistencies in reported figures from different sources. For emission factors, different fuel types, quality and combustion efficiency together contribute to the uncertainty. For example, coal used in China is of variable quality and so is its emission factors, *EF*, both before (raw coal) and after cleaning (cleaned coal) varies, which was found to cause a 15% uncertainty range for CO_2 emissions. On the other hand, there is limited temporal change of emission factors. For example, annual difference of emission factors for coal was within 2% globally[18] while the variation of emission factors, *EF*, for oil and gas was found to be much smaller.

Given the fact that uncertainty of fossil CO_2 emissions production is in general < ±10%[10,19,20], and the annual difference of emission factors is < 2%[18], CO_2 emissions during a few years period like Carbon Monitor can be estimated from absolute and relative change of activity through time, ignoring emissions factors changes. This method is used for updating changes of CO_2 emissions[1,21,22] [23], understanding that official and comprehensive CO_2 national inventories reported by countries to the UNFCCC only become available with a lag of two years for Annex-I countries and several years for non-Annex-I[24]. As such, a higher spatial, temporal and sectoral resolution of fossil CO_2 emissions than annual and national level can be obtained by using spatial, temporal and sectoral activity data to disaggregate annual national emissions[9,14,23,25]. The level of granularity depends on available data, such as location and operations of point sources[23] (i.e. power generation for a given plant), regional statistics of energy use (i.e. monthly fuel consumption) [9,25], and of proxies for the distribution of emissions such as population density, night lights, urban forms and GDP data …[9,14,23,25].

NEW Release of 8 Oct 2025

1) Using NGHGIs as baseline emissions

Instead of using a single baseline year (2019), we update the baseline emissions to cover the period 2019–2021. This update mainly relies on the national greenhouse gas inventories (NGHGIs) submitted to UNFCCC (**Table 1**), with IPCC sector emissions systematically mapped to the Carbon Monitor sectors.

Table 1 Data sources of baseline emissions in updated Carbon Monitor data.

Nation/Region	Reference Years (UNFCCC Submission)
Brazil, European Union, Japan, Russia, United States, United Kingdom	2019-2022 (BTR1)
China	2020-2021 (BTR1)
India	2019 (NC3), 2020 (BUR4)
ROW	2019-2022 (EDGAR_2025_GHG)

2) Updated activity data and methodology in the ROW region

We update the estimation for the power and industry sectors in the Rest of the World (ROW) region. To approximate emission changes in ROW, we use the average emission variations observed in countries with available data (**Table 2**). These countries represent 22% and 53% of total CO2 emissions in the ROW region, respectively.

Table 2 Countries with available data in ROW region.

Sector	Countries/regions
Power	Argentina, Australia, Bangladesh, Bolivia, Chile, Costa Rica, Dominican Republic, El Salvador, Georgia, Mexico, Moldova, New Zealand, Norway, Peru, South Africa, Switzerland, Turkey, Uruguay
Industry	Argentina, Bosnia and Herzegovina, Canada, Chile, Colombia, Indonesia, Israel, Republic of Korea, Malaysia, Mexico, Norway, Pakistan, Peru, Philippines, Qatar, Saudi Arabia, Serbia and Montenegro, Singapore, South Africa, Sri Lanka, Turkey, Ukraine, Uruguay, Viet Nam

Release of Carbon Monitor Europe

Carbon Monitor Europe daily CO2 emissions have been updated to May 31, 2022. The detailed dataset could be found at: https://eu.carbonmonitor.org/. The power sector of CM-EU has been updated to use fuel-specific emission factors.

There are some differences on emissions between EU27&UK and some EU countries of Global CM and those of CM-EU. The detailed reasons are as follows.

For the **power sector**, there are four EU countries (Lithuania, Luxembourg, Malta and Sweden) lacking power generation data. So we assume a linear relationship between their daily emissions and the total daily emissions of the 23 EU countries and the United Kingdom. The emissions of EU27&UK in CM-EU are the sum of all 28 countries. While the emissions of EU27&UK in global CM are directly based on annual emissions in 2019 and daily power generation data.

For the **industry sector**, the emissions in CM-EU are based on the country-level industry production index (IPI) from Eurostat. While global CM used the IPI seasonal adjusted from CEIC.

Release of 7 May 2022

Power sector:

Using fuel-specific emission factors

An update of country level power emission is calculated with country level activity data)

with fuel specific emission factors (EF*) for list of countries/regions including China, India, United States, EU27&UK, Japan, Brazil, United Kingdom, France, Germany, Italy and Spain, with the following equation:

$$Emis = \sum\sum(AD_{i,j} \times EF^{*}_{i,j})$$

Where i,j,k are indices for regions and fuel types respectively. The fuel specific emission factors are calculated by correcting corresponding generic IPCC emission factors (not country specific) with country specific baseline emissions (from 2019), with the following equations:

$$EF^{*}_{i,j} = EF_{j}^{IPCC} \times \frac{Emis_{i}^{2019-baseline}}{\sum(AD_{i,j}^{2019} \times EF_{i,j}^{IPCC})}$$

The fuel sources considered are coal, natural-gas and petroleum. The source for activity data comes from national grids as specified in the previous method description. The IPCC emission factors used for this analysis are: 820 gCO2/kWh for coal fired power, 490 gCO2/kWh for natural-gas fired power and 650 gCO2/kWh for petroleum fired power.

Updating the estimation in ROW countries

STEP1: estimating monthly emissions with available monthly electricity production data (total production or thermal production data are used, and the fuel-specific EFs are NOT applied) - *11 ROW countries/regions are available, contributing 46% of the total ROW CO2 emissions*
STEP2: disaggregating monthly emissions to daily level with available daily electricity production data (the thermal production data are used, and the fuel-specific EFs are NOT applied) - *2 ROW countries are available, contributing 9% of the total ROW CO2 emissions*

Industry sector :

Updating the estimation in ROW countries

STEP1: estimating monthly emissions with available monthly industrial production index (IPI) data - *23 ROW countries/regions are available, contributing 46% of the total ROW CO2 emissions*
STEP2: disaggregating monthly emissions to daily level by using the updated daily ROW power emission data

Ground transportation sector:

Updating activity data in China

As TomTom stopped collecting Chinese Data in April, 2020, in the previous versions, we extrapolated the time series of TomTom congestion level by repeating the data of the last week available. We are aware that this is a problem for us to track the emissions of China since that time. Now, we use the congestion level from AutoNavi Software Co., Ltd. (Gaode in Chinese) to replace TomTom when its data are not available. We compared Gaode congestion indices with TomTom ones and derived a method to harmonize the two products using the data from the common period (from Sep 2020 to Mar 2021). In the latest version of Carbon Monitor, we combined TomTom data for 2020 and Gaode data since 2021 into a harmonized time series. The emissions from the ground transportation sector for China were estimated based on this new time series. Compared with previous releases, the ground transportation emissions of China were thus changed.

Release of 28 October 2021

International shipping emission data update

The international shipping emissions are included in the ROW in the industry sector.

Release of 7 April 2021

U.S. emission data update

This is the first release of the state-level U.S. Carbon Monitor, using methods as follows:

State-level annual and monthly emissions based on EIA's energy data.

Annual total energy-related CO2 emissions by sector and source in 2018 for all the states in the U.S. are directly obtained from State Carbon Dioxide Emissions Data released by U.S. Energy Information Administration (EIA). We then disaggregate the state-level annual emissions in 2018 into monthly level based on monthly consumption data of key fuels (e.g., motor gasoline, diesel, jet fuel and natural gas) which are updated more frequently at state level from EIA . We assume that the emission factors remain unchanged for each state in 2019 and 2020 when comparing with 2018. We estimate state-level monthly emissions by sector in 2019 and 2020 based on the change of monthly consumption data of key fuels in 2019 and 2020 compared to the same period of 2018.

For the power sector, we use state-level monthly fuel-specific consumption data from Electric Power Monthly. For the industrial, residential and commercial sectors, we use state-level monthly natural gas consumption for each sector, with each fuel type

constrained by the trend of national-level total monthly consumption. For road transportation sector, we use prime supplier sales volumes of motor gasoline and diesel. For the aviation sector, we use prime supplier sales volumes of kerosene-type jet fuel.

State-level daily emissions in 2019 and 2020.

For 2019 and 2020, the state-level monthly emissions are allocated to each day by state-level daily indicators for each sector. For the power sector, we use state-level daily electricity generation produced by coal, petroleum and gas by summarizing the electricity produced of 63 balancing authorities from the EIA's Hourly Electric Grid Monitor (representing >93% of US electricity production). We remove the outliers and fill the missing values by using similar methods of Ruggles et al. (2020). For industrial sector, we use daily natural gas pipeline deliveries to industrial end users from Genscape.

For road transportation, we use daily distance traveled based on the Trips by Distance data from Bureau of Transportation Statistics. For the aviation sector, we use daily kilometers flown of flights (domestic and international) per state collected from the FlightRadar24 database. We classify the kilometers 255 flown per aircraft class (light, medium and heavy), with the emission factors per km flown of medium and large aircrafts are assumed to be 1.5 and 3 times that of small aircrafts. Emissions are attributed to the state of departure airport and are calculated separately for U.S. domestic flights and international flights departing from each state, with monthly totals rescaled according to jet fuel consumption.

For residential and commercial sector, we estimate daily emissions based on heating degree days (HDDs). We calculate daily and monthly population-weighted HDDs for each state based on the ERA5 reanalysis of 2-m air temperature. Residential and commercial emissions are split into heating emissions and cooking 2emissions: emissions from cooking are assumed to remain independent of temperature; emissions from heating are assumed to be a linear function of the heating demand (HDDs). A regression model based on monthly HDDs and monthly residential and commercial emissions in 2019 is developed to estimate the 9 annual percentage of emissions from heating demand in each state. We then estimate daily emissions in 2019 and 2020 based on changes in daily HDDs.

We have tried to correct the electricity use data and the natural gas consumption data of the residential and commercial sector for the temperature effect, i.e., energy consumption change caused by temperature change from year 2019 to year 2020. This was achieved by establishing linear regressions between monthly energy consumption and HDDs and CDDs (cooling degree days) for each state. Linear regression models are developed based on monthly energy consumption and monthly HDDs and CDDs data in 2019. Similar to previous studies, we include HDDs and CDDs in the regression models of electricity consumption, and CDDs only in the regression models of residential and commercial natural gas consumption. We then use the linear regression model and the temperature change between year 2020 and year 2019 (i.e., changes in HDDs and

CDDs on the same month of these 2 years) to calculate the corrected energy consumption for year 2020.

Data availability

All data sources for emissions estimates can be found in the Methods of Hong et al.: https://eartharxiv.org/repository/view/2233/. The energy data are obtained from EIA (https://www.eia.gov). The GDP data are from U.S. Bureau of Economic Analysis (https://apps.bea.gov/regional/downloadzip.cfm). The VMT data are from U.S. Department of Transportation (https://www.fhwa.dot.gov/policyinformation/travel_monitoring/tvt.cfm).

Data sources for the U.S. Carbon Monitor Project

Sector	Data type	Source
State-level monthly energy consumption data		
Power sector	fuel-specific consumption data	EIA Electricity (https://www.eia.gov/electricity/data/state/)
Industry sector	natural gas consumption	EIA Natural Gas (https://www.eia.gov/naturalgas/data.php)
Ground transportation	prime supplier sales volumes of motor gasoline and diesel	EIA Petroleum & Other Liquids (https://www.eia.gov/petroleum/data.php)
Aviation	prime supplier sales volumes of kerosene-type jet fuel	EIA Petroleum & Other Liquids (https://www.eia.gov/petroleum/data.php)
Residential and commercial	natural gas consumption	EIA Natural Gas (https://www.eia.gov/naturalgas/data.php)
State-level daily indicators		

Power sector	thermal generation produced by coal, petroleum and gas	EIA Hourly Electric Grid Monitor (https://www.eia.gov/beta/electricity/gridmonitor/)
Industry sector	pipeline deliveries to industrial end users	Genscape Natural Gas (https://www.genscape.com)
Ground transportation	distance traveled	Trips by Distance data from Bureau of Transportation Statistics (https://data.bts.gov/Research-and-Statistics/Trips-by-Distance/w96p-f2qv)
Aviation	kilometers flown of flights	FlightRadar24 database (https://www.flightradar24.com)
Residential and commercial	population-weighted heating degree days	ERA5 reanalysis of 2-meters air temperature (https://cds.climate.copernicus.eu/)

Update of baseline emissions in 2019

We update our baseline annual emissions in 2019 of each country and sectors based on the latest emission data release from EDGAR (https://edgar.jrc.ec.europa.eu/overview.php?v=booklet2020).

Release of 17 June 2020

Overview of Carbon Monitor daily CO_2 emissions production

Gaining from past experiences of constructing annual inventories and newly compiled activity data, Carbon Monitor is a novel daily dataset of CO_2 emissions from fossil fuel burning and cement production at national level. The countries/regions include China, India, U.S., Europe (EU27 & UK), Russia, Japan, Brazil, and rest of world (ROW), as well as the emissions from international bunker fuels from ships and aircraft. This dataset, known as Carbon Monitor, is separated into several key emission sectors: power sector (39% of total emissions), industrial production (28%), ground transport

(18%), air transport (3%), ship transport (2%), and residential consumption (10 %). For the first time, daily emissions estimates are produced for these six sectors, based on dynamically and regularly updated activity data. This is made possible by the availability of recent activity data such as hourly electrical power generation, traffic indices, airplane locations and natural gas distribution, with the assumption that the daily variation of emissions is driven by the activity data and that the contribution from emission factors is negligible, as they evolve at longer time scales, e.g. from policy implementation and technology shifts.

The framework of this study is illustrated in Fig 1. We calculated national CO_2 emissions and international aviation and shipping emissions since the Jan 1st 2019, drawing on hourly datasets of electricity power production and their CO_2 emissions in 29 countries (thus including the substantial variations in carbon intensity associated with the variable mix of electricity production), daily vehicle traffic indices in 416 cities worldwide, monthly production data for cement, steel and other energy intensive industrial products in 62 countries/regions, daily maritime and aircraft transportation activity data, and either previous-year fuel use data corrected for air temperature to residential and the commercial buildings. Together, these data cover almost all fossil fuels and industry sources of global CO_2 emissions, except for the emission from land use change (up to 10% of global CO_2 emissions) and non-fossil fuel CO_2 emissions of industrial products (up to 2% of global CO_2 emissions)[26] in addition to cement and clinker (i.e. plate glass, ammonia, calcium carbide, soda ash, ethylene, ferroalloys, alumina, lead and zinc etc.).

While daily emission can be directly calculated using near-real-time activity data and emission factors for the electricity power sector, such an approach is difficult to apply to all sectors. For the industry sector, emissions can be estimated monthly in some countries. For the other sectors, we used proxy data instead of daily real activity data, to dynamically downscale the annual or monthly CO_2 emissions totals on a daily basis. For instance, traffic indices in cities representative of each country were used instead of actual vehicle counts and categories, combined with annual national total sectoral emissions, to produce daily road transportation emissions. As such, for the road transportation, air transportation and residential use of fuels sectors in most countries, we downscaled monthly or annual total emission data in 2019 to calculate the daily CO_2 emission in the very year. Subsequently, we scaled monthly totals of 2019 by daily proxies of activities to obtain daily CO_2 emissions data in the first four months of 2020, during the unprecedented disturbance of the COVID-19 pandemic. The Carbon Monitor near-real-time CO_2 emission dataset shows a 7.8% decline of CO_2 emission globally from January 1st to April 30th in 2020 when compared with the same period in 2019, and detects a re-growth of CO2 emissions by late April which are mainly attributed to the recovery of economy activities in China and partial easing of lockdowns in other countries.

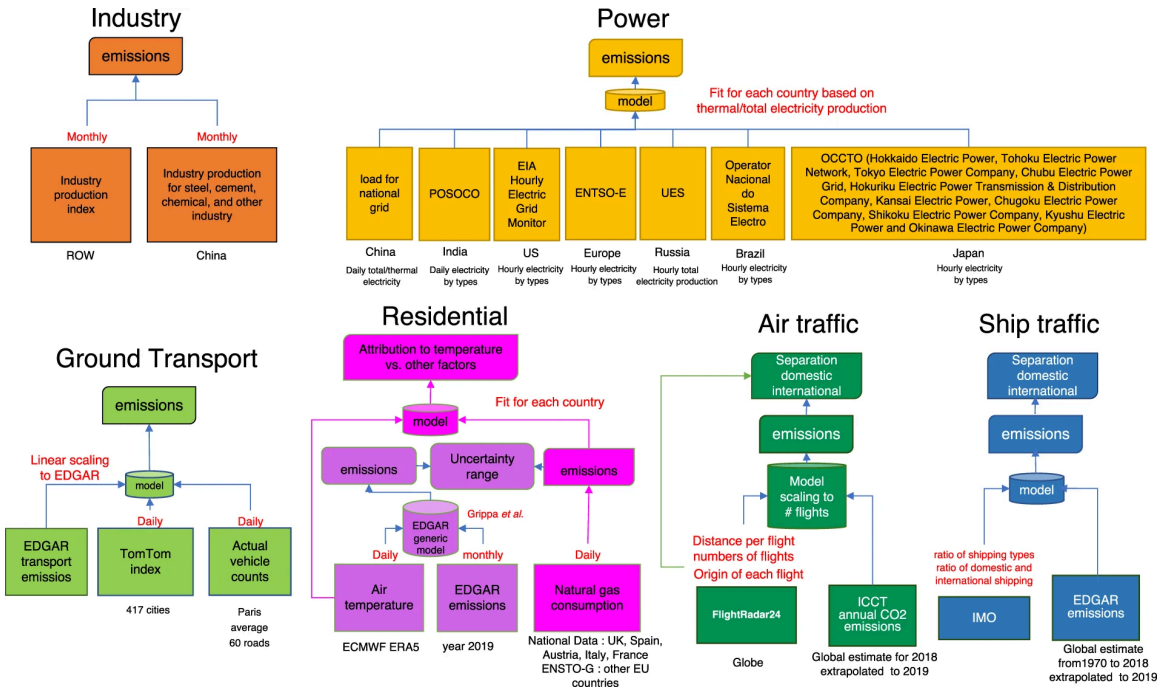

Fig 1. Overview of Carbon Monitor data production chain

Annual total and sectoral emissions per country / group of countries for the baseline year of 2019

According to the IPCC Guidelines for emission reporting[4], CO_2 emissions should be calculated by multiplying activity data by corresponding emission factors.

$$Emis = \sum\sum\sum(AD_{i,j,k} \cdot EF_{i,j,k}) \quad (1)$$

Where i, j, k are indices for regions, sectors and fuel types respectively. EF can be further separated into the net heating values v for each fuel type (the energy obtained per unit of fuel), the carbon content c per energy output (t C/TJ) and the oxidation rate o (the fraction (in %) of fuel oxidized during combustion):

$$Emis = \sum\sum\sum(AD_{i,j,k} \cdot (v_{i,j,k} \cdot c_{i,j,k} \cdot o_{i,j,k}) \quad (2)$$

Due to the lag of more than two years in publishing governmental energy statistics, we started from the latest CO_2 emissions estimates up to 2018 from current CO_2 databases[1,10-12]. For 2019, we completed this information to obtain annual total emissions

based on literature data and disaggregated the annual total into daily emissions (see below). For 2020, we estimated daily CO_2 emissions by using daily changes of activity data in 2020 compared to 2019. The CO_2 emissions and sectoral structure in 2019 for countries and regions were extracted from EDGAR V4.3.2[1,27] and V5.0 for each country, and national emissions were scaled to the year 2019 based on our own estimate (for China) and data from the Global Carbon Budget 2019[21] (for other countries):

$$Emis_{r,2019} = \alpha_r \cdot Emis_{r,2018} \quad (3)$$

For China, we firstly calculated CO_2 emissions in 2018 based on the energy consumption by fuel types and cement production in 2018 from China Energy Statistical Yearbook[28] and the National Bureau Statistics[29] following Equation 1. We projected the energy consumption in 2019 from the annual growth rates of coal, oil and gas reported by Statistical Communiqué[29] and applied China-specific emission factors [30] to obtain the annual growth rate of emissions in 2019. For US and Europe (EU27&UK), we used updated emission growth rates in 2019 published by CarbonBrief (https://www.carbonbrief.org/guest-post-why-chinas-co2-emissions-grew-less-than-feared-in-2019). For countries with no estimates of emission growth rates in 2019 such as Russia, Japan and Brazil, we assumed their growth rates of emissions was 0.5% based on the emission growth rate of the rest of world [22].

In this study, the EDGAR sectors were aggregated into four sectors (): power sector, industry sector, transport sector (ground transport, aviation and shipping), and residential sector. This is consistent with the new activity data we used below to compute daily variations. We used the sectoral distribution in 2018 from EDGAR to infer the sectoral emissions in 2019 for each country/region *r* (Equation 4), assuming that the sectoral distribution remained unchanged in these two years.

$$Emis_{r,s,2019} = Emis_{r,2019} \cdot \frac{Emis_{r,s,2018}}{Emis_{r,2018}} \quad (4)$$

Table 1 Scaling factors for the annual emission change in 2019 compared to 2018

Countries/Regions	**Scaling Factor (%)**	**Source**
China	2.8%	Estimated in this study
India	1.8%	Global Carbon Budget 2019[22]
US	2.4%	Carbon Brief, 2020
EU27&UK	-3.9%	Carbon Brief, 2020

Russia	0.5%	= ROW
Japan	0.5%	= ROW
Brazil	0.5%	= ROW
ROW	0.5%	Global Carbon Budget 2019[22]

According to IPCC Guidelines[4], CO_2 emissions for each sector should be calculated by multiplying sectoral activity data by their corresponding emission factors following Equation 5:

$$Emis_s = AD_s \cdot EF_s \quad (5)$$

The emissions were calculated following this equation separately for the power sector, the industry sector, the transport sector, and the residential sector, as explained in the following.

Daily power sector (electricity production) CO_2 emissions

The CO_2 emissions from the power sector were calculated by adapting Equation 5 with sector specific activity data (i.e. electricity production/thermal electricity production) and corresponding emission factors (Equation 6).

$$Emis_{power} = AD_{power} \cdot EF_{power} \quad (6)$$

Normally the emission factors change slightly over time but can be assumed to remain constant over the two years period considered in this study, compared to the huge changes in activity data. Thus, we assumed that emission factors remained unchanged in 2019 and 2020, and calculated the daily emissions as follows:

$$Emis_{daily} = Emis_{yearly} \cdot \frac{AD_{daily}}{AD_{yearly}} \quad (7)$$

The data sources of daily activity data in the power sector are described as Table 2. The countries/regions listed in Table 2 account for more than 70% of the total CO_2 emissions in the power sector. For emissions from other countries (ROW), which are not listed in Table 2, we estimated the power sector emission changes in 2020 based on the period of the national lock-down. For daily emission changes of ROW in 2019, we firstly assumed a linear relationship between daily global emission and daily total emissions of the ROW countries listed in Table 2. Then we classified each country according to

whether they adopted lock-down measures, based on official reports. Based on daily emission data of the power sector of the countries listed in Table 2, we calculated the respective average change rates of power sectors in ROW countries between January and April, assuming changes started since the date of lock-down in each country. Emissions from countries with no lock-down were left unchanged. We then applied these country-specific January to April emissions growth rates to estimate daily changes for each ROW country in 2020, based on their lock-down measures, and aggregated them into daily emission for ROW.

Table 2 Data sources of activity data for estimating power sector emissions

Country/Region	**Data source**	**Sectors included**	**Resolution**
China	National Grid Daily Electric Load	Thermal production	Daily
India	Power System Operation Corporation Limited (https://posoco.in/reports/daily-reports/)	Thermal production (summarizing the production of *Coal*, *Lignite*, and *Gas, Naphtha & Diesel*)	Daily
US	Energy Information Administration's (EIA) Hourly Electric Grid Monitor (https://www.eia.gov/beta/electricity/grid monitor/)	Thermal production (summarizing the production of *Coal, Petroleum,* and *Natural Gas*)	Hourly
EU27 & UK	ENTSO-E Transparency platform (https://transparency.entsoe.eu/dashboard/show)	Thermal production (summarizing the production of *Fossil.Brown.coal.Lignite, Fossil.Coal.derived.gas, Fossil.Gas, Fossil.Hard.coal, Fossil.Oil, Fossil.Oil.shale,* and *Fossil.Peat*.)	Croatia, Cyprus, Ireland, Luxembourg and Malta excluded due to unsatisfactory data quality or missing data
Russia	United Power System of Russia (http://www.so-ups.ru/index.php)	Total generation	Hourly

Japan	Summarizing electricity data from 10 electricity providers 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).	Total generation	Hourly
Brazil	Operator of the National Electricity System (http://www.ons.org.br/Paginas/).	Thermal production	Hourly

Daily industrial production and cement production CO_2 emissions

While daily production data is not directly available for industrial and cement production, the monthly CO_2 emissions from industry and cement production sector could be calculated by using monthly statistics of industrial production, and daily data of electricity generation to disaggregate the monthly CO_2 emissions into daily values. This calculation assumes a linear relationship between daily electricity generation for industry and daily industry production data to compute daily industry production.

The emissions from industrial production during the fossil fuel combustion were calculated by multiplying activity data (i.e., fossil fuel consumption data in the industrial sector) by corresponding emission factors by type of fuel. Due to limited data availability, we assumed a linear relationship between daily industrial production and industrial fossil fuel use, and the emission factors remaining unchanged. So, the monthly emissions in 2019 in country/region could be calculated by following equation:

$$Emis_{monthly,2019,r} = Emis_{yearly,2019,r} \cdot (P_{monthly,2019,r}/P_{yearly,2019,i,r}) \qquad (8)$$

Emissions from cement production during the chemical process of calcination of calcite were calculated with the same Eq.(8), which is normally used by multiplying the cement production by the emission factor of this industry.

Specifically, for China, the emissions from the industry sector were further divided into steel industry, cement industry, chemical industry, and other industries (indicated by index i):

$$Emis_{monthly,2019,China} = \sum Emis_{,2019,i} \cdot (P_{monthly,2019,i}/P_{yearly,2019,i}) \quad (9)$$

For monthly emissions in 2020 in country/region *r*, we used the following equation:

$$Emis_{monthly,2019,r} = Emis_{monthly,2019,i} \cdot (P_{monthly,2020,r}/P_{monthly,2019,r}) \quad (10)$$

where is the industrial production in different industrial sectors (in China) or a total Industrial Production Index (in other countries) as listed in Table 3. In China's case, the January and February estimates were combined as no individual monthly data was reported by sources listed in Table 3 for these two months. The monthly industrial emissions were disaggregated to daily emissions using daily electricity data, as explained above.

Lacking the latest Industrial Production Index in April 2020 for Europe, India, Japan, Russia and Brazil, we adopted monthly growth rates of industrial output from Trading Economics (https://tradingeconomics.com) based on preliminary survey data. For other countries not listed in Table 3, we used the same method as described for the power sector to calculate the daily industry emissions from ROW.

To allocate monthly emissions into daily emissions, we used the weight of daily electricity production to monthly electricity production, as daily industry data were not available

$$Emis_{daily} = Emis_{monthly} \cdot (Elec_{daily}/Elec_{monthly}) \quad (11)$$

Table 3 Data sources for industrial production

Country/Region	Sector	Data	Data source
China	Steel ndustry	Crude steel production	World Steel Association website (https://www.worldsteel.org/)
	Cement Industry	Cement and clinker production	National Bureau of Statistics (http://www.stats.gov.cn/english/)

	Chemical ndustry	sulfuric acid, caustic soda, soda ash, ethylene, chemical fertilizer, chemical pesticide, primary plastic and synthetic rubber	National Bureau of Statistics (http://www.stats.gov.cn/english/)
	Other ndustry	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, plain glass, ten kinds of nonferrous metals, refined copper, ead, zinc, electrolyzed aluminum, industrial boilers, metal smelting equipment, and cement equipment	National Bureau of Statistics (http://www.stats.gov.cn/english/)
India	'	Industrial Production Index (IPI)	Ministry of Statistics and Programme Implementation (http://www.mospi.nic.in)
US	'	Industrial Production Index (IPI)	Federal Reserve Board (https://www.federalreserve.gov)
EU & UK	'	Industrial Production Index (IPI)	Eurostat (https://ec.europa.eu/eurostat/home)
Russia	'	Industrial Production Index (IPI)	Federal State Statistics Service (https://eng.gks.ru) Trading Economics (https://tradingeconomics.com)
Japan	'	Industrial Production Index (IPI)	Ministry of Economy, Trade and Industry (https://www.meti.go.jp) Trading Economics (https://tradingeconomics.com)
Brazil	'	Industrial Production Index (IPI)	Brazilian Institute of Geography and Statistics (https://www.ibge.gov.br/en/institutional/the-ibge.htm) Trading Economics

(https://tradingeconomics.com)

Daily road transportation CO_2 emissions

We collected hourly TomTom congestion level data from the TomTom website (https://www.tomtom.com/en_gb/traffic-index/). The congestion level (called hereafter) represents the extra time spent on a trip, in percentage, compared to uncongested condition. TomTom congestion level data were obtained for 416 cities across 57 countries at a temporal resolution of one hour. Of note that a zero-congestion level means that the traffic is fluid or 'normal', but does not mean there was no vehicle and zero emissions. It is thus important to identify the lower threshold of emissions when the congestion level is zero. To do so, we compared the time series of daily mean TomTom

congestion level, with the daily mean car flux (called Q hereafter in vehicle per day) from publicly available real-time data from an average of 60 roads in the Paris megacity. Those daily mean car counts were reported by the City's service (https://opendata.paris.fr/pages/home/). We used a sigmoid function to fit the relationship between and (Fig 2):

$$Q = a + \frac{bX^c}{d^c + X^c} \tag{12}$$

where a, b, c and d are the regression parameters (Table 4). We verified that the empirical fit from Eq. (12) can reproduce the observed large drop due to the lockdown in Paris and the recovery afterwards. We assume that daily emissions relative changes were proportional to the relative change of the function from Eq. (12). Then, we applied the function established for Paris to other cities included in the TomTom dataset, assuming that the relative magnitude in car counts (and thus emissions) follow a similar relationship with TomTom. The emission changes were first calculated for individual cities, and then weighted by city emissions to aggregate to national changes. For a specific country i with n cities reported by TomTom, the national daily vehicle flux for day j was given by:

$$Q_{country,dayj} = \frac{\sum_{i=1}^{n} Q_{i,dayj} E_i}{\sum_{i=1}^{n} E_i} \tag{13}$$

Where E_i is the annual road transportation emission of city *n* taken in the grid point of each TomTom city from the annual gridded EDGARv4.3.2 emission map for the "road transportation" sector (1A3b) (httpiis://edgar.jrc.ec.europa.eu/) for the year 2010, assuming that the spatial distribution of ground transport did not change significantly within a country between 2010 and the period of this study. Then, the daily road

transportation emissions in 2019 and 2020 ($E_{country,dayj}$) for a country were scaled such that the total road transportation emissions in the first four months of 2019 equaled to 121/365 times the annual emissions of this sector in 2019 ($E_{country,2019}$) estimated in this study:

$$E_{country,dayj} = Q_{country,dayj} \frac{121/365 \times E_{country,2019}}{\sum_{j=1}^{182} Q_{country,dayj(2019)}} \quad (14)$$

For countries not included in the TomTom dataset, we assumed that the emission changes follow the mean changes of other countries. For example, Cyprus, as an EU member country, had no city reported in TomTom dataset, so its relative emission change was assumed to follow the same pattern of the total emissions from other EU countries included in TomTom dataset (which covers 98% of EU total emissions). Similarly, the relative emission changes of countries in ROW but not reported by TomTom were assumed to follow the same pattern of the total emissions from all TomTom reported countries (which cover 85% of global total emissions).

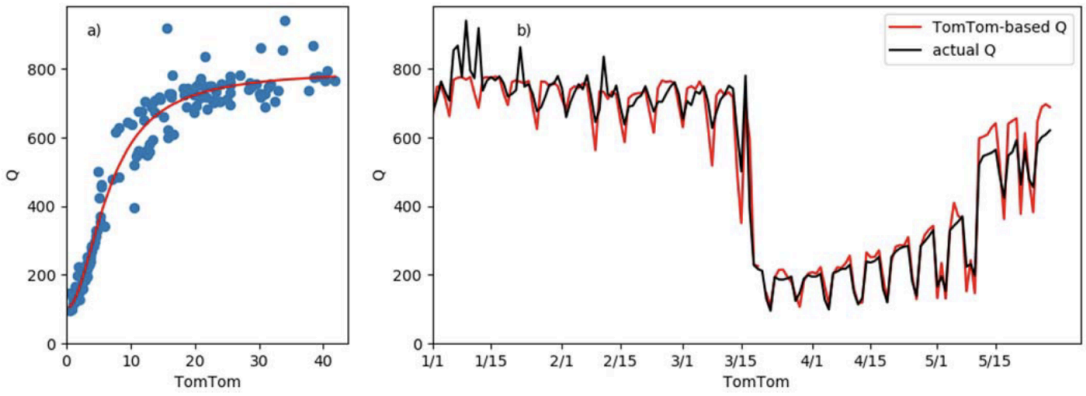

Fig 2 (a) Relationship between TomTom congestion level index and actual car counts (Q) for Paris. The sigmoid fit between and is given by the red line. (b) evaluation of the function during the period of the lock down in Paris.

Table 4 Regression parameters of the sigmoid function of Eq. (12) that describes the relationship between car counts () and TomTom congestion level

Parameter	Value
a	100.87
b	671.06
c	1.98

d	6.49

Table 5 Cities (416 across 57 countries) with TomTom congestion level data

untry/Region	**y**
stria (5)	nna, Salzburg, Graz, Innsbruck, Linz
gium (10)	ssels, Antwerp, Namur, Leuven, Ghent, Liege, Kortrijk, Mons, Bruges, Charleroi
garia (1)	ia
ech (3)	o, Prague, Ostrava
nmark (3)	penhagen, Aarhus, Odense
onia (1)	inn
land (3)	sinki, Turku, Tampere
nce (25)	is, Marseille, Bordeaux, Nice, Grenoble, Lyon, Toulon, Toulouse, Montpellier, ntes, Strasbourg, Lille, Clermont-Ferrand, Brest, Rennes, Rouen, Le-havre, nt-Etienne, Nancy, Avignon, Orleans, Le-mans, Dijon, Reims, Tours
rmany (26)	nburg, Berlin, Nuremberg, Bremen, Stuttgart, Munich, Bonn, Frankfurt-am-main, sden, Cologne, Wiesbaden, Ruhr-region-west, Leipzig, Hannover, Kiel, Freiburg, sseldorf, Karlsruhe, Ruhr-region-east, Munster, Augsburg, Monchengladbach, nnheim, Bielefeld, Wuppertal, Kassel
eece (2)	ens, Thessaloniki
ngary (1)	dapest
and (1)	ykjavik
and (3)	olin, Cork, Limerick
y (25)	me, Palermo, Messina, Genoa, Naples, Milan, Catania, Bari, Reggio-calabria, ogna, Florence, Turin, Prato, Cagliari, Pescara, Livorno, Trieste, Verona, Taranto, ggio-emilia, Ravenna, Padua, Parma, Modena, Brescia
via (1)	a
uania (1)	ius
embourg (1)	embourg
herlands (17)	e-hague, Haarlem, Leiden, Arnhem, Amsterdam, Rotterdam, Nijmegen, Groningen, dhoven, Utrecht, Amersfoort, Tilburg, Breda, Apeldoorn, Zwolle, Den-bosch, Almere

way (4)	o, Trondheim, Stavanger, Bergen
and (12)	lz, Krakow, Poznan, Warsaw, Wroclaw, Bydgoszcz, Gdansk-gdynia-sopot, zecin, Lublin, Bialystok, Bielsko-biala, Katowice-urban-area
tugal (5)	ɔon, Porto, Funchal, Braga, Coimbra
mania (1)	charest
ssia (11)	scow, Saint-petersburg, Novosibirsk, Yekaterinburg, Nizhny-novgorod, Samara, stov-on-don, Chelyabinsk, Omsk, Tomsk, Kazan
vakia (2)	tislava, Kosice
venia (1)	ɔljana
ain (25)	celona, Palma-de-mallorca, Granada, Madrid, Santa-cruz-de-tenerife, Seville, oruna, Valencia, Malaga, Murcia, Las-palmas, Alicante, Santander, Pamplona, ɔn, Cordoba, Zaragoza, Vitoria-gasteiz, Vigo, Cartagena, Valladolid, Bilbao, Oviedo, n-sebastian, Cadiz
eden (4)	ckholm, Uppsala, Gothenburg, Malmo
itzerland (6)	neva, Zurich, Lugano, Lausanne, Basel, Bern
key (10)	ınbul, Ankara, Izmir, Antalya, Bursa, Adana, Mersin, Gaziantep, Konya, Kayseri
aine (4)	v, Odessa, Kharkiv, Dnipro
(25)	nburgh, London, Bournemouth, Hull, Belfast, Brighton-and-hove, Bristol, nchester, Leicester, Coventry, Nottingham, Cardiff, Birmingham, Southampton, eds-bradford, Liverpool, Sheffield, Swansea, Newcastle-sunderland, Glasgow, ading, Portsmouth, Stoke-on-trent, Preston, Middlesbrough
ypt (1)	ro
uth Africa (6)	ɔe-town, Johannesburg, Pretoria, East-london, Durban, Bloemfontein

Table 5 (continued) Cities (416 across 57 countries) with TomTom level data

Country/Region	City
China (22)	Chongqing, Zhuhai, Guangzhou, Beijing, Chengdu, Changchun, Changsha, Shenzhen, Shenyang, Shanghai, Wuhan, Fuzhou, Shijiazhuang, Xiamen, Nanjing, Hangzhou, Tianjin, Ningbo, Quanzhou, Dongguan, Suzhou, Wuxi

Hong Kong (1)	Hong Kong
India (4)	Mumbai, New-delhi, Bangalore, Pune
Indonesia (1)	Jakarta
Israel (1)	Tel-aviv
Japan (5)	Tokyo, Osaka, Nagoya, Sapporo, Kobe
Kuwait (1)	Kuwait-city
Malaysia (1)	Kuala-lumpur
Philippines (1)	Manila
Saudi Arabia (2)	Riyadh, Jeddah
Singapore (1)	Singapore
Taiwan (5)	Kaohsiung, Taipei, Taichung, Tainan, Taoyuan
Thailand (1)	Bangkok
United Arab Emirates (2)	Dubai, Abu-dhabi
Australia (10)	Sydney, Melbourne, Brisbane, Adelaide, Gold-coast, Hobart, Newcastle, Perth, Canberra, Wollongong
New Zealand (6)	Auckland, Wellington, Hamilton, Christchurch, Dunedin, Tauranga
Argentina (1)	Buenos-aires
Brazil (9)	Recife, Sao-paulo, Rio-de-janeiro, Salvador, Fortaleza, Porto-alegre, Belo-horizonte, Curitiba, Brasilia
Chile (1)	Santiago
Columbia (1)	Bogota
Peru (1)	Lima
Canada (12)	Vancouver, Toronto, Montreal, Ottawa, London, Winnipeg, Halifax, Quebec, Hamilton, Calgary, Edmonton, Kitchener-waterloo
Mexico (1)	Mexico-city

USA (80)	Los-angeles, New-york, San-francisco, San-jose, Seattle, Miami, Chicago, Washington, Honolulu, Atlanta, Baton-rouge, San-diego, Boston, Austin, Portland, Philadelphia, Sacramento, Houston, Riverside, Tampa, Nashville, Orlando, Charleston, Denver, Cape-coral-fort-myers, Pittsburgh, New-orleans, Las-vegas, Boise, Fresno, Baltimore, Tucson, Providence, Charlotte, Dallas-fort-worth, Oxnard-thousand-oaks-ventura, Bakersfield, Greenville, Jacksonville, Detroit, Albuquerque, Columbus, San-antonio, Salt-lake-city, Phoenix, Mcallen, Raleigh, Virginia-beach, Hartford, Colorado-springs, Birmingham, New-haven, Louisville, Minneapolis, Cincinnati, El-paso, Allentown, Buffalo, Memphis, Worcester, Grand-rapids, Albany, St-louis, Milwaukee, Omaha-council-bluffs, Indianapolis, Rochester, Columbia, Oklahoma-city, Cleveland, Tulsa, Kansas-city, Knoxville, Richmond, Winston-salem, Dayton, Little-rock, Syracuse, Akron, Greensboro-high-point

Daily commercial aviation CO_2 emissions

We calculated CO_2 emissions from commercial aviation following a commonly used approach: reconstructing the emission inventories from bottom up based on the knowledge of the parameters of individual flights. We collected the FlightRadar24 data (https://www.flightradar24.com/) for the departure and landing airports for each flight, the calculate the distance flown assuming the shortest distance for each flight, and then CO_2 emissions per flight[31]. Flights were grouped per country, and for each country between domestic or international traffic. The daily CO_2 emission was computed as the product of distance flown, by a CO_2 emission factor per *km* flown, according to:

$$Daily\ Emis_{aviation} = Daily\ Kilometers\ Flown_{aviation\ 2020} \times EF_{aviation\ 2019} \quad (14)$$

We acquired monthly individual commercial flight information from FlightRadar24. Individual commercial flights are tracked by FlightRadar24 based on reception of ADS-B signals emitted by aircraft and received by their network of ADS-B receptors[31].

The are computed assuming great circle distance between the take-off, cruising, descent and landing points for each flight and are cumulated over all flights. As there is no sufficient data available to convert the FlightRadar24 database into CO_2 emissions on a flight-by-flight basis, we computed CO_2 emissions by assuming a constant CO_2 emission factor per km flown across the whole fleet of aircraft (regional, narrowbody passenger, widebody passenger and freight operations). This assumption is justified if the mix of flights between these categories has not changed substantially between 2019 and 2020.

$$Daily\ Emis_{2020} = Daily\ Emis_{2019} \times \frac{Daily\ Kilometers\ Flown_{2020}}{Daily\ Kilometers\ Flown_{2019}} \quad (15)$$

EDGAR published an estimate of total CO_2 emissions from commercial aviation in 2018 of 925 Mt CO_2. And the International Council on Clean Transportation (ICCT) implied annual compound growth rate of total emissions from commercial flights, 5.7%, during the past five years from 2013 to 2018[32]. In the absence of further information, we considered this increase to be representative of the emission growth rate of commercial aviation from 2018 to 2019. The FlightRadar24 database has incomplete data for some flights and may miss altogether a small fraction of actual flights[31], so we scaled the EDGAR estimate of CO_2 emissions (inflated by 5.7% for the year 2019) with the total estimated number of kilometers flown in 2019 (67.91 million km) and apply this scaling factor to 2020 data. We assumed that the fraction of missed flights was the same in 2019 and 2020, which is reasonable.

Daily ship traffic CO_2 emissions

We collected international CO2 ships emissions from 2016-2018 based on the EDGAR's international emissions. We also. collected global shipping emissions during the period of 2007-2015 from IMO[33] and ICCT (https://theicct.org/sites/default/files/publications/Global-shipping-GHG-emissions-2013-2015_ICCT-Report_17102017_vF.pdf). According to the Third IMO GHG Study[33], CO2 emissions from international shipping accounted for 88% of global shipping emissions, domestic and fishing accounts for 8% and 4%, respectively. We calculated international CO2 shipping emissions from 2007-2015 from global shipping emissions and the ratio of international shipping and global shipping emissions. We extrapolated emissions from linear fits 2007-2018 to estimate the emissions in 2019. The data sources of shipping emissions are in Table 6. We obtained emissions for the first quarter of 2019 based on the assumption the equal distribution of monthly shipping CO_2 emissions. The equations are as follows:

$$Monthly\ Emis_{international\ shipping,2019} = \alpha \times Yearly\ Emis_{international\ shipping,201} \quad (16)$$

α is the increasing rate of international shipping emissions in 2019 based on the linear extrapolation of data from the period 2007-2018, estimated to be of 3.01%. represents the ratio of the months to be calculated in the whole year. Given this, we estimated the shipping emissions for the first quarter of 2019, equals 121/365.

We assumed that the change in shipping emissions was linearly related to the change in ships. Traffic volume. The change of international shipping emissions for the first four months of 2020 was calculated according to the following equation:

$$Emis_{period,2020} = Emis_{period,2019} \times C_{index} \quad (17)$$

Where C_{index} represents the ratio of the change in shipping emissions, estimated to the end of Apr by -15% compared to the same period of last year according to https://www.theedgemarkets.com/article/global-container-shipments-set-fall-30-next-few-months.

Table 6. Data sources used to estimate ship emissions

Shipping Emissions	Sources
Global shipping Emissions (2007-2012)	IMO[33]
Global shipping Emissions (2013-2015)	ICCT
International shipping Emissions (2016-2018)	EDGAR v5.0

Daily residential sector emissions CO_2 emissions, from residential and commercial buildings

Fuel consumption daily data from this sector are not available. Several studies (ref) showed that the main source of daily and monthly variability of this sector is climate, namely heating emissions increase when temperature falls below a threshold which depends on region, building types and people habits. We calculated emissions by assuming annual totals unchanged from 2019 and using climate daily climate information, in three steps: 1) estimation of population-weighted heating degree days for each country and for each day based on the ERA5[34] reanalysis of 2-meters air temperature, 2) split residential emissions into two parts: cooking emissions and heating emissions according to the EDGAR database[35], using the EDGAR estimates of 2018 residential emissions as the baseline. Emissions from cooking were assumed to remain independent of temperature, and those from heating were assumed to be a function of the heating demand. Based on the change of population-weighted heating degree days in each country in 2019 and 2020, we downscaled annual EDGAR 2018 residential emissions to daily values for 2019 and 2020 as described by Eq. 18-20:

$$Emis_{c,m} = Emis_{c,m,2018} \times \frac{\sum_{m} HDD_{c,d}}{\sum_{m,2018} HDD_{c,d}} \quad (18)$$

$$Emis_{c,d} = Emis_{c,m} \times Ratio_{heating,c,m} \times \frac{HDD_{c,d}}{\sum_{m} HDD_{c,d}} + Emis_{c,m} \times (1 - Ratio_{heating,c} \quad (19)$$

$$HDD_{c,d} = \frac{\sum(Pop_{grid} \times (T_{grid,c,d} - 18))}{\sum(Pop_{grid})} \quad (20)$$

where c is country, d is day, m is month, $Emis_{c,m}$ is the residential emissions of country c in month m of the year 2019 or 2020, $Emis_{c,m,2018}$is the emissions of country c in month m of the year 2018, $HDD_{c,d}$ is the population-weighted heating degree day in country c in day d, is the residential emissions of country c in day d of the year 2019 or 2020, $Ratio_{heating,c,m}$ is the percentage of residential emissions from heating demand in country c in month m, N_m is the number of days in month m, Pop_{grid} is gridded population data derived from Gridded Population of the World, Version 4[36], T is the daily average air temperature at 2 meter derived from ERA5[34].

The main assumption is this approach is that residential emissions did not change from other factors than heating degree days variations in 2020, when people time in houses dramatically increased during the lockdown period. In order to test the validity of this assumption, we compiled natural gas daily consumption data by residential and commercial buildings for France (https://www.smart.grtgaz.com/fr/consommation) (unfortunately such data could not be collected in many countries) during 2019 and 2020. Natural gas consumption in kWh per day was transformed to CO_2 emissions using an emission factor of 10.55 kWh per m^3 and a molar volume of 22.4 10^{-3} m^3 per mole.

Firstly, we verified that the temporal variation of those 'true' residential CO_2 emissions was similar to that given by equations (18) to (20). Secondly, after fitting a piecewise model to those natural gas residential emission data using ERA5 air temperature data, we removed the effect of temperature to obtain an emission corrected for temperature effects. Even if the lock down was very strict in France, we found no significant emission anomaly, meaning that the fact that nearly the entire population was confined at home did not increase or decrease emissions. This complementary analysis tentatively suggests that residential emissions can be well approximated in other countries by equations (18) to (20) based only on temperature during the lockdown period.

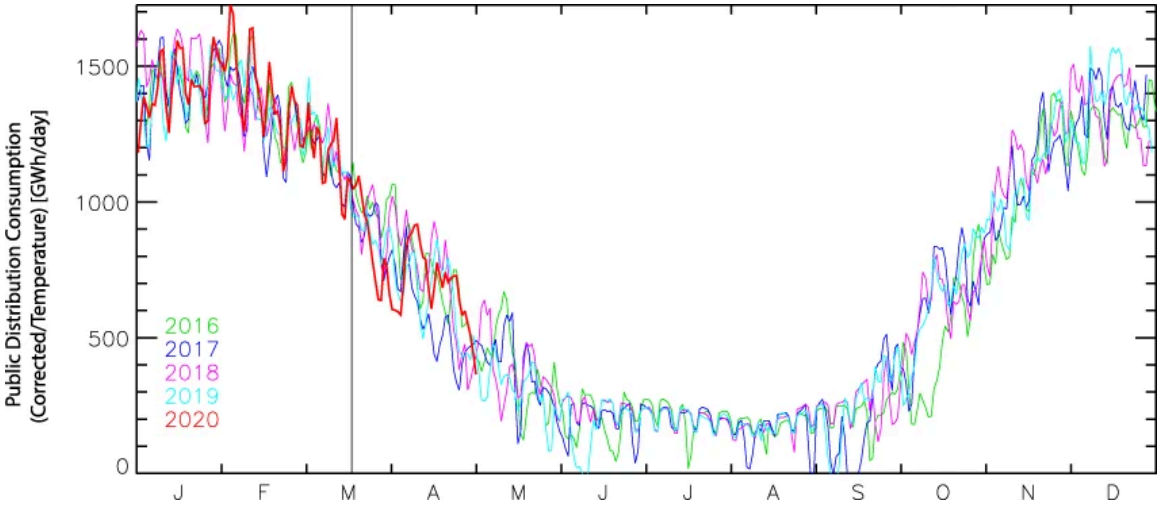

Fig 3. Residential and commercial building daily natural gas consumption (linearly related to CO_2 emissions from this sector) in France for the last 5 years. Temperature effects have been removed from emissions using a linear piecewise model. When the effect of variable winter temperature was accounted for, no significant change is seen in 2020 during the very strict lock-down period.

Data Records and list of countries and groups of countries

Currently there are 27484 data records provided in this dataset:

- 268 records are daily mean CO_2 emissions (from fossil fuel combustion and cement production process) 1751-2020.
- 4374 records are the daily emissions for 9 countries or groups of countries as given in Table 7 (China, India, US, EU27&UK, Russia, Japan, Brazil, ROW and Globe) and 486 days (from January 1st 2019 to April 30th 2020).
- 22842 records are daily emissions in power sector, ground transport sector, industry sector, residential sector, aviation sector and international shipping sector respectively, for 9 countries/regions (China, India, US, EU27&UK, Russia, Japan, Brazil, ROW and Globe) and 486 days (from January 1st 2019 to April 30th 2020).

Table 7. Countries or group of countries abbreviations used on the web site

WLD	World (all countries or groups of countries)
CHN	People's Republic of China
BRA	Brazil
EU28	European Union 27 in 2020
FRA	France
DEU	Germany
IND	India
ITA	Italy
JPN	Japan
RUS	Russia
ESP	Spain
USA	United States
GBR	United Kingdom
ROW	Rest of the World

Estimation of CO_2 emissions uncertainties

We followed the 2006 IPCC Guidelines for National Greenhouse Gas Inventories to conduct the uncertainty analysis of the data (1-sigma uncertainties).

Power sector: uncertainty is mainly from inter-annual variability of coal emission factors. Based the UN statistics the inter-annual variability of fossil fuel is within (±1.5%), which been used as uncertainty of the CO_2 emissions from this sector.

Industrial sector: uncertainty comes from the monthly production data. Given that CO_2 emissions from industry and cement production in China accounts for more than 60% of world total industrial CO_2, and the fact that uncertainty of emission in China is t Uncertainty

from monthly statistics was derived from 10000 Monte Carlo simulations to estimate a 68% confidence interval (1-sigma) for China. from monthly statistics was derived from 10000 Monte Carlo simulations to estimate a 68% confidence interval (1-sigma) for China. 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. 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[37], 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.

Road Transportation: emissions from this sector is estimated by assuming that the relative magnitude in car counts (and thus emissions) follow the similar relationship with TomTom. Emissions 1-sigma uncertainties were quantified by the prediction interval of the regression.

Commercial Aviation: Uncertainties in the aviation CO2 emissions are difficult to assess. Sources of uncertainties arise from the ICCT (2018) estimate used to scale emissions, the lack of completeness of the flight database and the fixed average conversion factor between kilometers flown and CO_2 emissions. These last two uncertainties should have a limited impact as we do not expect a change between 2019 and 2020 in database completeness and in the average fleet composition. In the study 1-sigma uncertainty of aviation sector was approximated from the difference of daily emission data estimated based on the two methods. We calculated the average difference between the daily emission results estimated based on the flight route distance and the number of flights, and then divide the average difference by the average of the daily emissions estimated by the two methods to obtain the uncertainty of CO_2 from aviation sector.

Shipping: We used the uncertainty analysis from IMO as our uncertainty estimate for shipping emissions. According to Third IMO Greenhouse Gas study 2014[33], the uncertainty of shipping emissions was set to 13% based on this inventory.

Residential sector (commercial and residential buildings): The 1-sigma uncertainty in daily emissions are estimated as 20%, which is calculated based on the comparison with daily residential emissions derived from real fuel consumptions in several European countries including France, Great Britain, Italy, Belgium, and Spain.

Global annual 2019 emissions: The 1-sigma uncertainty of emission projection in 2019 is estimated as 2.2%, by combining the reported uncertainty of the projected growth rates and the EDGAR estimates in 2018.

Overall uncertainty: We combined all the uncertainties from each sector (Table 8) by following the error propagation equation from IPCC. Eq. (21) is used to derive for the uncertainty of the sum, which could be used to combine the uncertainties of all sectors:

$$U_{total} = \frac{\sqrt{\Sigma(U_s \cdot \mu_s)}}{\left|\Sigma \mu_s\right|} \quad (21)$$

Where and are the percentage uncertainties and the uncertain quantities (daily mean emissions) of sector respectively. Eq. (22) was used to derive for the uncertainty of the multiplication, which is used to combine the uncertainties of all sectors and of the projected emissions in 2019:

$$U_{overall} = \sqrt{\Sigma U_i^2} \quad (22)$$

Table 8 Percentage 1-sigma uncertainties of all items.

Items	**Uncertainty Range**
Power	±1.5%
Ground Transport	±9.3%
Industry	±36.0%
Residential	±40.0%
Aviation	±10.2%
International Shipping	±13.0%
Projection of emission growth rate in 2019	±0.8%
EDGAR emissions in 2018	±5.0%
Overall	**±6.8%**

Code Availability

The code generated during and/or analyzed during the current study are available from the corresponding author. After peer-reviewed the code will be open accessible on the Carbon Monitor website (www.carbonmonitor.org or www.carbonmonitor.org.cn).

References.

1 Janssens-Maenhout, G. *et al.* EDGAR v4. 3.2 Global Atlas of the three major Greenhouse Gas Emissions for the period 1970–2012. *Earth System Science Data* **11**, 959-1002 (2019).

2 Marland, G. & Rotty, R. M. Carbon dioxide emissions from fossil fuels: a procedure for estimation and results for 1950-1982. *Tellus B: Chemical and Physical Meteorology* **36**, 232-261 (1984).

3 Intergovernmental Panel on Climate Change (IPCC). Revised 1996 IPCC Guidelines for National Greenhouse Gas Inventories. (1997).

4 Intergovernmental Panel on Climate Change (IPCC). *2006 IPCC Guidelines for National Greenhouse Gas Inventories*. (Intergovernmental Panel on Climate Change, 2006).

5 Marland, G. & Rotty, R. M. Carbon dioxide emissions from fossil fuels: A procedure for estimation and results for 1950–1982. *Tellus B* **36**, 232-261 (1984).

6 Gregg, J. S., Andres, R. J. & Marland, G. China: Emissions pattern of the world leader in CO2 emissions from fossil fuel consumption and cement production. *Geophys. Res. Lett.* **35**, L08806, doi:10.1029/2007gl032887 (2008).

7 Andres, R. J., Boden, T. A. & Higdon, D. A new evaluation of the uncertainty associated with CDIAC estimates of fossil fuel carbon dioxide emission. *Tellus B* **66** (2014).

8 Fridley, D. Inventory of China's Energy-Related CO2 Emissions in 2008. *Lawrence Berkeley National Laboratory* (2011).

9 Andres, R. J., Gregg, J. S., Losey, L., Marland, G. & Boden, T. A. Monthly, global emissions of carbon dioxide from fossil fuel consumption. *Tellus B: Chemical and Physical Meteorology* **63**, 309-327 (2011).

10 Le Quéré, C. *et al.* Global carbon budget 2018. *Earth System Science Data* **10**, 2141-2194 (2018).

11 BP. BP Statistical Review of World Energy 2018 www.bp.com › bp › corporate › pdfs › energy-economics,. (2018).

12 International Energy Agency (IEA). *CO2 Emissions from Fuel Combustion 2019* *https://www.iea.org/reports/co2-emissions-from-fuel-combustion-2019*. (2019).

13 Hong, C. *et al.* Variations of China's emission estimates: response to uncertainties in energy statistics. *Atmospheric Chemistry and Physics* **17**, 1227-1239 (2017).

14 Crippa, M. *et al.* High resolution temporal profiles in the Emissions Database for Global Atmospheric Research. *Scientific Data* **7**, 121, doi:10.1038/s41597-020-0462-2 (2020).
15 Zhao, Y., Zhou, Y., Qiu, L. & Zhang, J. Quantifying the uncertainties of China's emission inventory for industrial sources: From national to provincial and city scales. *Atmospheric Environment* **165**, 207-221 (2017).
16 Andres, R. J. *et al.* A synthesis of carbon dioxide emissions from fossil-fuel combustion. *Biogeosciences* **9**, 1845-1871 (2012).
17 Olivier, J. G., Janssens-Maenhout, G. & Peters, J. A. *Trends in global CO2 emissions: 2013 report*. (PBL Netherlands Environmental Assessment Agency, 2013).
18 Liu, Z. *et al.* Reduced carbon emission estimates from fossil fuel combustion and cement production in China. *Nature* **524**, 335-338 (2015).
19 Olivier, J. G. & Peters, J. Trends in global CO2 and total greenhouse gas emissions https://www.pbl.nl/sites/default/files/downloads/pbl-2020-trends-in-global-co2-and-total-greenhouse-gas-emissions-2019-report_4068.pdf. *PBL Netherlands Environmental Assessment Agency* **5** (2019).
20 Andres, R. J., Boden, T. A. & Higdon, D. M. Gridded uncertainty in fossil fuel carbon dioxide emission maps, a CDIAC example. *Atmospheric Chemistry and Physics (Online)* **16** (2016).
21 Asefi‐Najafabady, S. *et al.* A multiyear, global gridded fossil fuel CO2 emission data product: Evaluation and analysis of results. *Journal of Geophysical Research: Atmospheres* **119**, 10,213-210,231 (2014).
22 Friedlingstein, P. *et al.* Global carbon budget 2019. *Earth System Science Data* **11**, 1783-1838 (2019).
23 Oda, T., Maksyutov, S. & Andres, R. J. The Open-source Data Inventory for Anthropogenic CO2, version 2016 (ODIAC2016): a global monthly fossil fuel CO2 gridded emissions data product for tracer transport simulations and surface flux inversions. *Earth Syst. Sci. Data* **10**, 87-107, doi:10.5194/essd-10-87-2018 (2018).
24 Eggleston, S., Buendia, L., Miwa, K., Ngara, T. & Tanabe, K. *2006 IPCC guidelines for national greenhouse gas inventories*. Vol. 5 (Institute for Global Environmental Strategies Hayama, Japan, 2006).
25 Gregg, J. S. & Andres, R. J. A method for estimating the temporal and spatial patterns of carbon dioxide emissions from national fossil-fuel consumption. *Tellus B: Chemical and Physical Meteorology* **60**, 1-10 (2008).
26 Cui, D., Deng, Z. & Liu, Z. China’s non-fossil fuel CO2 emissions

from industrial processes. *Applied Energy* **254**, 113537 (2019).
27 Crippa, M. *et al.* Fossil CO2 and GHG emissions of all world countries. *Luxemburg: Publication Office of the European Union* (2019).
28 National Bureau of Statistics. *China Energy Statistical Yearbook*. (China Statistical Press, 2019).
29 National Bureau of Statistics. *Statistical Communiqué of the People's Republic of China on the National Economic and Social Development*, <http://www.stats.gov.cn/tjsj/tjgb/ndtjgb/> (2020).
30 Liu, Z. *et al.* Reduced carbon emission estimates from fossil fuel combustion and cement production in China. *Nature* **524**, 335-338, doi:10.1038/nature14677 (2015).
31 FlightRadar24. (2020).
32 Brandon Graver, K. Z., Dan Rutherford. ICCT CO2 commercl aviation, 2018. (2019).
33 Smith, T. W. P. *et al.* Third IMO Greenhouse Gas Study 2014. (2015).
34 Copernicus Climate Change Service (C3S), E. F. g. o. E. a. r. o. t. g. c., Copernicus Climate Change Service Climate Data Store (CDS), https://cds.climate.copernicus.eu/. ERA5: Fifth generation of ECMWF atmospheric reanalyses of the global climate, Copernicus Climate Change Service Climate Data Store (CDS), https://cds.climate.copernicus.eu/. (2017).
35 Crippa, M. *et al.* Fossil CO2 and GHG emissions of all world countries - 2019 Report. Report No. JRC117610, (Luxembourg, 2019).
36 Doxsey-Whitfield, E. *et al.* Taking advantage of the improved availability of census data: a first look at the gridded population of the world, version 4. *Papers in Applied Geography* **1**, 226-234 (2015).
37 Liu, Z., Zheng, B. & Zhang, Q. New dynamics of energy use and CO2 emissions in China. *arXiv preprint arXiv:1811.09475* (2018).