Errors and uncertainties associated with the use of unconventional activity data for estimating CO2 emissions

Tomohiro Oda[1], Chihiro Haga[2], Kotaro Hosomi[2], Takanori Matsui[2], and Rostyslav Bun[3]

[1]Universities Space Research Association
[2]Osaka University
[3]Lviv Polytechnic National University

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Abstract

CO2 emissions from fossil fuel combustion (FFCO2) can be robustly estimated from fuel used (as activity data, AD) and CO2 emissions factor, due to the nature of FFCO2. Recent traffic emission changes under the impact of the COVID-19 pandemic have been estimated using emerging non-fuel consumption data, such as human mobility data that tech companies reported as AD, due to the unavailability of timely fuel statistics. The use of such unconventional activity data (UAD) might allow us to provide emission estimates in near-real time; however, the errors and uncertainties associated with such estimates are expected to be larger than those of common FFCO2 inventory estimates, and thus should be provided along with a thorough evaluation/validation of the methodology and the resulting estimates. Here, we show the impact of COVID-19 on traffic CO2 emissions over the first six months of 2020 in Japan. We calculated CO2 monthly emissions using fuel consumption data and assessed the emission changes relative to 2019. Regardless of Japan's soft approach to COVID-19, traffic emissions significantly declined by 23.8% during the state of emergency in Japan (April-May). We also compared relative emission changes among different estimates available. Our analysis suggests that UAD-based emission estimates during April and May could be biased by -19.6% to 12.6%. We also used traffic count data for examining the performance of UAD as a proxy for traffic and/or CO2 emissions. We found traffic changes are not proportional enough to emission changes to allow emissions to be estimated with accuracy, and moreover, the traffic-based approach failed to capture emission seasonality. Our study highlighted the challenges and difficulties in the use of limited non-scientific data for modeling human activities and assessing the impact on the environment, and the importance of a thorough error and uncertainty assessment before using these data in policy applications.

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Tomohiro Oda[1,2,3], Chihiro Haga[3], Kotaro Hosomi[4], Takanori Matsui[3] and Rostyslav Bun[5,6]

1 The Earth from Space Institute (EfSI), Universities Space Research Association, Columbia, MD, US
2 Department of Atmospheric and Oceanic Science, University of Maryland, College Park, MD, US
3 Graduate School of Engineering, Osaka University, Osaka, Japan
4 School of Engineering, Osaka University, Osaka, Japan
5 Lviv Polytechnic National University, Lviv, Ukraine
6 WSB University, Dąbrowa Górnicza, Poland

Corresponding author: Tomohiro Oda (toda@usra.edu)

Abstract

CO_2 emissions from fossil fuel combustion (FFCO2) can be robustly estimated from fuel used (as activity data, AD) and CO_2 emissions factor, due to the nature of FFCO2. Recent traffic emission changes under the impact of the COVID-19 pandemic have been estimated using emerging non-fuel consumption data, such as human mobility data that tech companies reported as AD, due to the unavailability of timely fuel statistics. The use of such unconventional activity data (UAD) might allow us to provide emission estimates in near-real time; however, the errors and uncertainties associated with such estimates are expected to be larger than those of common FFCO2 inventory estimates, and thus should be provided along with a thorough evaluation/validation of the methodology and the resulting estimates.

Here, we show the impact of COVID-19 on traffic CO_2 emissions over the first six months of 2020 in Japan. We calculated CO_2 monthly emissions using fuel consumption data and assessed the emission changes relative to 2019. Regardless of Japan's soft approach to COVID-19, traffic emissions significantly declined by 23.8% during the state of emergency in Japan (April-May). We also compared relative emission changes among different estimates available. Our analysis suggests that UAD-based emission estimates during April and May could be biased by -19.6% to 12.6%. We also used traffic count data for examining the performance of UAD as a proxy for traffic and/or CO_2 emissions. We found traffic changes are not proportional enough to emission changes to allow emissions to be estimated with accuracy, and moreover, the traffic-based approach failed to capture emission seasonality. Our study highlighted the challenges and difficulties in the use of limited non-scientific data for modeling human activities and assessing the impact on the environment, and the importance of a thorough error and uncertainty assessment before using these data in policy applications.

Keywords: CO_2, fossil fuel CO_2 emission, COVID-19, IPCC, emission inventory, activity data

1 Introduction

Carbon dioxide (CO_2) emissions from fossil fuel combustion (FFCO2) are the main drivers of the observed atmospheric CO_2 growth (e.g. Prentice *et al* 2001). Since the time of the industrial revolution, human beings have added 400 trillion metric tons of CO_2 into the atmosphere by burning fossil fuels, such as coal, oil and natural gas (Gilfillan *et al* 2020). Under the Paris Climate Agreement (e.g. UNFCCC 2021a), the world set the 1.5/2.0 degree C temperature goal and aims to achieve the goal by the mid 21st century, which requires significantly reducing greenhouse gas (GHG) emissions, including CO_2 as well as other major GHG gases, to net zero GHG emissions (or carbon/climate neutral) (e.g. Reville 2016, Marland *et al* 2019, UNFCCC 2021b). The Paris Agreement recognizes the subnational contributions to the climate actions. Quantifying emissions at subnational levels, which is beyond the scope of the current IPCC inventory system, is thus the critical central skill for assessing and monitoring the emission reduction effort towards the Paris Agreement goal.

Estimates of FFCO2 are often from fuel statistics (e.g. Marland and Rotty 1984, IPCC 2006, Andres *et al* 2011, 2012). According to the emission compilation guideline defined by the Intergovernmental Panel on Climate Change (IPCC), GHG emissions from a country (or a system of interest) can be calculated as a product of socio-economic activity data (AD) and emission factor (EF) (IPCC 2006):

$$Emission = AD \times EF \quad \text{--- (1)}$$

The robustness of the FFCO2 estimates from the calculation is mainly supported by the use of the total fuels used/combusted within the system boundary. Given that CO_2 does not chemically change after oxidation/combustion, FFCO2 from a country (or system) of interest can be robustly estimated by multiplying the amount of fossil fuels burned by the emission factor. In this way (defined as reference approach in the IPCC guideline), country-level FFCO2 estimates can be obtained in a relatively quick manner using available fuel statistics, then compared to ones from the sectoral approach, which requires additional socio-economic sectoral disaggregation of statistical data (e.g. IPCC 2006). The robustness of the estimates from the fuel-based approach is due to the fact that AD captures the source of carbon emissions within a system boundary well. For major sectors of FFCO2, such as energy production and traffic, the IPCC guideline suggests using the fuel statistics, which are often available for a country on an annual basis, and they are considered to be robust due to economic incentive (IPCC 2006). Therefore, annual emissions are often estimated by projecting the emission estimates for the most recent year using fuel statistical data (e.g. Myhre *et al* 2009, Oda *et al* 2018) with reasonably small estimation errors, regardless of the revisions to the statistical data (Friedlingstein *et al* 2020).

Recent studies (e.g. Le Quéré *et al* 2020a, Forster *et al* 2020, Liu *et al* 2020a, 2020b) employed innovative approaches to estimate daily emissions for the year 2020 and attempted to assess the impact of COVID-19 on human emissions. While there are differences among the methodologies and data used, those studies essentially extrapolated their reference emissions using unconventional non-fuel statistics AD, such as power plant operational data, economic indices, traffic congestion data and/or relevant indices that could indicate the traffic volume changes, and mobility data collected by tech companies, such as Apple Inc. and Google LLC, in order to estimate sectoral emission changes with a focus on the lockdown periods. Those studies have been the primary source for CO_2 emission estimates under COVID-19, and have been used in a number of studies, including the recent United Nations (UN)'s Emission Gap Report (UNEP 2020) and the Global Carbon Balance report (Friedlingstein *et al* 2020). Also, several studies have used the near-real-time estimates for modeling applications (e.g. Zeng *et al* 2020, Weir *et al* 2020) where COVID-19 impacts are examined using atmospheric observations in combination with atmospheric modeling.

While the near-real-time estimates were obtained in the same way as defined in eq. (1), the use of UAD and the emission information it aims to provide is beyond the scope of the IPCC guideline (annual country scale). Thus, the use of UAD should have been carefully evaluated, as suggested by the IPCC good practice guideline, since the validity of the use of UAD has not been assessed. Especially since the robustness of annual national emissions has been supported by the use of fuel data, the performance of UAD in the emission calculation at a time scale (daily) beyond what the guideline sets forth is the key for the robustness of their estimates. The use of UAD could open up a new path for providing near-real time emission estimates. However, such emission information should be provided with conservative uncertainty estimates, since the errors and uncertainties are expected to be larger than ones for our common FFCO2 estimates.

This study reports monthly CO_2 emissions from the transportation (traffic) sector in Japan for the first six months of the year 2020, which includes the period of Japan's state of emergency (7^{th} of April - 27^{th} of May, Prime Minister of Japan and His Cabinet 2020a, 2020b), and presents the impact of COVID-19 on the emissions using the 2019 emissions as a baseline. Our estimates are based on the fuel consumption data collected by a Japanese government agency and the common inventory calculation suggested by the IPCC guideline. We also examine the use of UAD for estimating CO_2 emissions. We consider our estimates as the best estimate solely by the method and data we used, as discussed earlier, and thus use them as a reference/truth to evaluate the performance of the UAD, such as Apple and Google data as well as traffic data, as an estimator for CO_2 emission changes. We also assess the performance of Apple and Google data as an estimator of traffic count data and examine the assumption, commonly made in the recent studies, that CO_2 emissions are proportional to traffic changes. We also compare our estimates to the recent near-real-time estimates in order to assess the accuracy and characterize/quantify possible errors and biases.

2 Method

2.1 Fuel-based emission calculation

We estimated monthly traffic CO_2 emissions using fuel consumption data for the first six months of 2020 and all of 2019 (total 18 months). We used the monthly fuel consumption data for automobile use collected by the Ministry of Land, Infrastructure, Transport and Tourism (MLIT) (MLIT 2021). The monthly fuel consumption data are reported for four fuel categories, such as gasoline, diesel, Liquified Propane Gas (LPG), and Liquified Natural Gas (LNG). Following the IPCC guideline (IPCC 2006), we calculated monthly traffic CO_2 emissions as follows:

$$Emission = \sum_a [Fuel_a \times EF_a] \quad \text{--- (2)}$$

where *Fuel* is the amount of the fuel (fuel type *a*) consumed, and EF_a is the emission factor for the fuel type a. We used country-specific EFs provided by the Ministry of the Environment, Japan (see values presented in Table S1 in Supplement Information). From a methodological point of view, our estimates can be considered to be the best estimates possible since they use the official fuel statistical data and country-specific EF values (Tier 2 emission estimates in the IPCC definition). Thus, our estimates serve as the truth in this study when other estimates are examined, as well as a reference to allow errors and uncertainties to be calculated in terms of deviations from our estimates.

2.2. Unconventional, Activity Data (UAD)-based emission calculation

While the usage of the UAD in the recent studies, such as Le Quéré *et al* (2020a) and Liu *et al* (2020a), (2020b), are not exactly the same, the basic assumption in those studies is that changes in the activity levels are proportional to the emissions. The estimation can be done as follows:

$$Emission\ (t) = UAD(t) \times E_{ref} \quad \text{--- (3)}$$

The emissions in the recent studies are estimated by scaling the reference (or baseline) emission (E_{ref}) using the relative change in UAD at time t. We obtained emission values by scaling our January fuel-based emission estimate using monthly relative changes indicated by UAD, as shown in the eq. (3). We collected two UAD that have been used in the previous publications (e.g. Le Quéré *et al* 2020a, Forster *et al* 2020), such as Apple's Mobility Trends Reports (Apple Inc. 2021) and Google's COVID-19 Community Mobility Reports (Google LLC 2021), as well as actual traffic count data.

Apple's Mobility Trends Report (hereafter, Apple data) is based on data sent from users' devices to the Maps app service. Apple data is published on a daily basis and reports daily changes in requests for directions on the Maps app by three transportation types (driving, transit, and walking) for several spatial levels, such as countries/regions, sub-regions and cities (Apple Inc. 2021). The values were normalized by the value on the day 13 of January 2020. We used values reported for driving in Japan. Day in the Apple data is defined as midnight-to-midnight, Pacific time. However, we used the values as reported without any adjustment. The daily values before the day 13 of January (baseline) were assumed to be the same as the baseline (value = 100, which means no changes from the baseline). The values for the 11th and 12th of May, which were missing, were set as an average of the values for the 10th and 13th of May.

Google's COVID-19 Community Mobility Reports (hereafter, Google data) are similar to the Apple data, but intend to show how people's movements change compared to a baseline (Google LLC 2021). The baseline was defined as the median values for the corresponding day of the week, during 3rd of January to 6th of February 2020 (5-week period). The mobility trends are reported for six categories, such as grocery & pharmacy, parks, transit stations, retail & recreation, residential, and workplaces. Following Forster *et al* (2020), we used values reported for the transit stations category. We are aware that the Google data has been updated over the past year. Thus, the values used in this study might not be exactly the same as ones used in Forster *et al* (2020).

The traffic count data we used in this study were collected from a nation-wide automated system. The raw traffic measurement (count) data were being collected at approximately 39k locations (an average of our study period) at a 5-min interval and compiled by Japan's National Police Agency. The data are provided through the Japan Road Traffic Information Center (JARTIC) (JARTIC 2021). We calculated the national monthly total traffic counts for the first six months of 2020 and the entire year of 2019 (total eighteen months). We then used the relative changes from January to scale our January fuel-based estimate. We also used traffic count data for two additional purposes in this study: (1) to evaluate the performance of Apple and Google data as a proxy for traffic count and (2) examine the performance of traffic data as an estimator of CO_2 emissions. (see 2.3)

We also collected the recent near-real time estimates made by Le Quéré *et al* (2020a) and Liu *et al* (2020a) and included in the emission comparison/evaluation in this study.

2.3. Error and Uncertainty assessment

The percent uncertainty U associated with the emission estimate from eq. (1) can be calculated as

$$U = \sqrt{U_{AD}^2 + U_{EF}^2} \quad \text{--- (4)}$$

where U_{AD} is the percent uncertainty for AD and U_{EF} is the percent uncertainty for the EF (IPCC 2006). Using the reported uncertainty estimates for the fuel data and EF (5%, 2 sigma for both), the uncertainty for our emission estimates is calculated as 7% (2 σ).

Similarly, the uncertainty of the UAD estimates could be calculated in the way as seen in eq. (4) as a combination of the percent uncertainties by replacing the U_{EF} with the uncertainty estimates of the reference emissions U_{Ref}.

$$U = \sqrt{U_{UAD}^2 + U_{Ref}^2} \quad \text{--- (5)}$$

U_{Ref} could be assessed using the uncertainty estimates provided for the original estimates. If U_{Ref} is obtained by disaggregating original estimates in time or space, one might need to add the associated disaggregation uncertainty and/or error (Oda *et al* 2015, 2019). As described in 2.2, our UAD-based estimates share E_{Ref}, which is our January fuel-based estimate, and thus, we focus on the assessment of U_{UAD}. Another reason that we focus on the assessment of U_{UAD} is because E_{Ref} in eq (3) is often subject to systematic errors due to revisions to the underlying statistical data (Marland *et al* 2009, Andres *et al* 2014) and/or errors in them (Guan *et al* 2012). E_{Ref} will be updated when the new statistical data become available, while UAD is likely to remain the same. Such systematic errors are not often explicitly included in the common uncertainty. An example of an exception is the assessment done by Andres *et al* (2014) for the global total emission estimates. The U_{UAD} is often not directly measurable and any alternative data to serve as truth does not exist; the nature of proxy makes it more difficult to evaluate (Oda *et al* 2019). However, in this study, we could attempt to evaluate U_{UAD} by comparing UAD (Apple and Google data) to traffic data as the UAD was used as a proxy for traffic under the assumption that traffic volume is proportional to emission changes. We acknowledge that our assessment is not able to separate uncertainties in AD and errors due to the performance of AD, thus our estimate of UAD should include both.

We also identify uncertainties that are not captured in eq. (5), namely uncertainties associated with the emission calculation (or model). Such uncertainties include (1) conceptualization uncertainty and (2) model uncertainty (IPCC 2006). Following the suggestions from the IPCC guideline, we will examine those two uncertainties, which are often poorly characterized or may not be characterized at all, as seen in the recent near-real time estimates. We should be able to approach the uncertainties using our fuel-based estimates as a reference in combination with the traffic data. For example, the conceptualization uncertainty could be assessed by comparing the traffic-based estimates to the fuel-based estimates and the uncertainty should show up as the differences. The traffic-based estimates can be viewed as the case where UAD is the perfect estimator of traffic data. The model uncertainty due to the incomplete model representation could be examined by comparing UAD to traffic data, as described earlier. Errors and uncertainties associated with the mismatch of the system boundary in the calculation and spatial and temporal representativeness of UAD are difficult to clearly define, but should be captured in this assessment.

The sources of errors and uncertainties discussed here are challenging to disentangle and assess and provide statistically meaningful error and uncertainty estimates individually. This study attempts to assess them where possible. We also acknowledge there is no perfect single metric to show these degrees of errors and uncertainties, and thus we calculate and provide multiple metrics. The set of assessments we deliver in this study essentially corresponds to the QA/QC and Verification activities suggested by the IPCC guideline as a *good practice* (IPCC 2006). The IPCC guideline suggests that these assessment activities could happen not only after obtaining the emissions, but also during the emission development process. By doing so, one could obtain robust estimates by capturing error/uncertainty sources as much as possible and potentially mitigate them where possible.

3 Results

Traffic emissions in Japan during the first six month of the year 2020

Our monthly emission estimates are shown in Figure 1 (2020 as blue solid line with dots, and 2019 dashed grey line, the calculated emission values are shown in Table S2 in Supplement Information). A summary of the emission comparisons is shown in Table 1. Our fuel-based calculation shows that the total traffic CO_2 emission for the first six months of 2020 was 80.6 $MtCO_2$, which was 11.4% lower than the total emissions from the same six-month period in 2019 (90.9 $MtCO_2$). While the 2020 emissions started at the same level as the 2019 January emission (the difference was only 1.5%), the 2020 emissions started deviating from the 2019 reference values in March, and showed significant decline in April and May when Japan's state of emergency was in place (7th of April -6th of May, and then extended to 27th of May). Japan's state of emergency did not impose a physical lockdown for identified severe areas (seven prefectures), and the core of Japan's approach has been to prevent the spread of the pandemic by avoiding the "Three Cs: Closed spaces, Crowded places, and Close-contact settings" (Government of Japan 2020) with a target of reducing the contact by 70-80% (Prime Minster of Japan and His Cabinet 2020c). Japan's government asked their citizens and businesses to reduce the activity level, while maintaining the necessary businesses thorough citizens' efforts rather than forcing them by penalty or fines (Prime Minster of Japan and His Cabinet 2020c). Essentially, the measures to decrease the spread of the virus were voluntary. Thus, Japan's approach to the COVID-19 pandemic has been considered to be a soft approach compared to ones taken in many other countries. Its performance has been analyzed and discussed (e.g. Normile 2020, Feder 2020, Wingfiel-Hayes 2020, Gordon 2020, Nishimura 2020). In light of the "soft" approach, the emission reduction confirms that the citizens and businesses reduced the level of their economic activity in response to the request under the state of emergency. The mean emission reduction during the two months was 23.8% relative to the 2019 level.

So how well was the emission reduction captured by the UAD-based approaches? Figure 1 also compares several values derived using UAD, such as traffic count (green), Apple data (pink), and Google data (dark green) and evaluates the performance of UAD for estimating emissions. In the figure, the errors due to the use of UAD are manifested as a deviation from our fuel-based approach. Table 1 shows several calculated metrics, such as R^2, bias, and mean absolute error (MAE). Here, the traffic-based emissions also can help us to examine the performance of Apple and Google data as a proxy for traffic volume or estimator of CO_2 emissions. Apple and Google data are used in the recent publications and thus this comparison should allow us to characterize the recent estimates in terms of the use of UAD, while our calculations do not fully replicate their daily values precisely. As described in the Method section, all the monthly values were obtained by scaling the same January fuel-based emission estimate. Thus, we can focus solely on the relative changes estimated by different UADs.

We confirmed that all the UAD indicated the decrease in the activity, thus the resulting emissions decreased towards the period of the state of emergency and started recovering in June. However, our comparison shows the emission seasonalities derived from different UADs can vary by a large degree (R^2 = 0.54 - 0.93; Bias = -11.2 - 11.0%; MAE = 10.6 - 12.7%, see Table 1). For example, the traffic count data and Apple data seem to be systematically overestimating the emissions in comparison to our fuel-based estimates (reference). Both cases show an increase in February, especially in Apple data. The traffic volume in January is typically lower than other months, due to the significantly lower traffic volume during the New Year time in Japan (23% lower than the day 13 reference level in 2020). We speculate that the emission increase from January to February could be partially explained by the low traffic volume in January, while the traffic volume should have returned to normal level by the reference day for the Apple (13th of January). Also, as noted by Apple, Inc. (2021), the relative volume increase since January 13th is consistent with their normal, seasonal usage of the Apple Maps app in many countries/regions, sub-regions, and cities. While we are unable to identify the reason, these could show up as a significant overestimation in February and March, which is a good characteristic as a proxy for traffic (R^2 = 0.75, see Table S2 in Supplemental Information), but not for CO_2 (R^2 = 0.54).

The emission seasonality from the Google data is closer to our fuel estimates (R^2 = 0.93) than that from the Apple data (R^2 = 0.54), and did not have the overestimation seen in the traffic-based estimates and Apple data-based estimates in February and correctly indicated the start of the emission decline in March, but significantly overestimated the emission reduction (by 9.9%). Just by looking at the values reported for the other five categories (see Figure S2 in Supplemental Information), the "workplaces" or "retail and recreation," or the average of them could be an excellent estimator of CO_2. On the other hand, "grocery and pharmacy" and "parks" seem to be in better agreement with the monthly traffic changes. The adequate information to understand and explain this is not available for evaluation due to the nature of the data provided (privacy policy), this shows a challenge of the use of UAD as a proxy, and the need for the evaluation of their performance. While the choice of "transit stations" for the CO_2 estimation does make sense, the "workplaces" might not be the best estimator of traffic. However, it was not a big issue and the performance as an estimator for CO_2 is more concerning.

Figure 1 also compares our fuel-based estimates to the recent near-real-time estimates, such as Le Quéré *et al* (2020a) (median values as solid, high values as dotted, and low values as dashed) and Liu *et al* (2020a) or the Carbon Monitor (Liu *et al* 2020b). We found that Carbon Monitor underestimated the emission reduction by 9.1% and Le Quéré *et al* (2020a) study overestimated the emission reduction by 7.9% (median case) during the period of Japan's state of emergency. The Le Quéré *et al* (2020) estimates (also see daily estimates shown in Figure S3 in Supplemental Information) show very different monthly changes from the Apple data case we created. We speculate that the Confinement Index (CI) function used in Le Quéré *et al* (2020a) must have had a strong impact in their near-real-time calculation. The CI was defined based on the policy implemented, rather than quantitative information (Le Quéré *et al* 2020a). Emission estimations based on the information from expert judgement further makes the error and uncertainty assessment challenging. Interestingly, the Carbon Monitor emission change is a significantly good agreement with the one based on Traffic (R^2= 0.95), rather than with our fuel-based estimates. The regressed sinusoidal function model, which was calibrated to the Paris data (Liu *et al*

2020b), seems to be a good estimator of traffic change in Japan at the national level, but not so much for CO_2 we had hoped.

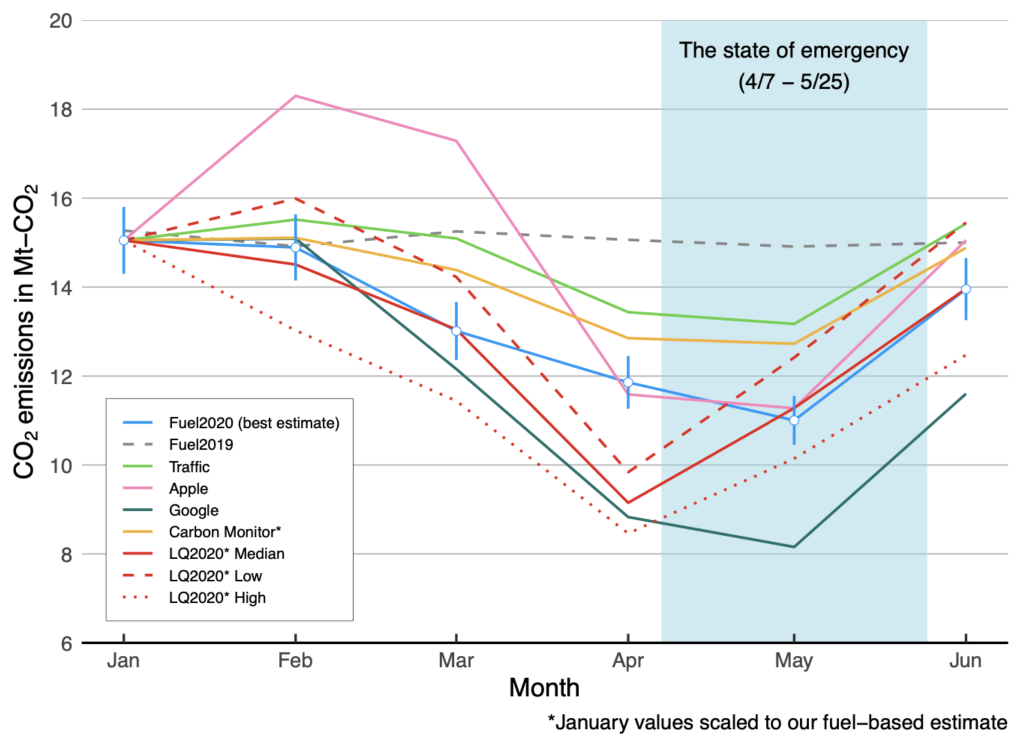

Figure 1. The year 2020 monthly traffic CO_2 emission estimates in Japan. The blue line indicates emission estimates based on monthly fuel consumption data, which is considered to be the best monthly estimate solely by the method and data used. The error bars indicate the two sigma uncertainty range (5%). The grey dashed line indicates the 2019 monthly fuel-based emissions as a reference to show the emission reduction level in 2020, including the period of Japan's state of emergency (7th April - 25th May 2020). The green line indicates values obtained by scaling the January fuel-based estimate using monthly traffic volume changes relative to January. The pink and dark green lines are obtained in the same way using the Apple Mobility data (driving) and the Google COVID-19 report (transit stations), which served as the activity data (AD) examined and used in Le Quéré *et al* (2020a) and Forster *et al* (2020). The yellow line indicates monthly estimates taken from the Carbon Monitor (https://carbonmonitor.org/, Liu *et al* 2020b). The three red lines indicate the estimates made by Le Quéré *et al* (2020a) as denoted as LQ2020. The solid line shows the median values, and the dashed and dotted lines show the high case and low case respectively. All the emission values are given in the unit of $MtCO_2$/month. To eliminate the impact of the days in a month, emission values are expressed as $MtCO_2$/30days, where one month is uniformly represented by 30 days regardless of actual days of the month. Monthly total emission values are shown in Figure S1 and also listed in Table S2.

Table 1. A summary of the metrics to show the performance of those estimates. R^2, bias (in %) and Mean Absolute Error (MAE, in %) are presented to give an idea of the performance of the existing estimates. Bias and MAE are calculated using the Fuel-based estimates (best estimates) as reference. The estimates of the total emission reductions are also calculated for different estimates (also in %). The CO_2 estimates with an asterisk are adjusted using our fuel-based January emission estimates. The numbers in the parenthesis are biases (in %). The emission values and other metrics mentioned in the main text are listed in Table S2.

CO2 estimates	Fuel (Ref)	UAD-based estimates			Near-real time estimates			
		Traffic	Apple	Google	LQ2020* (Median)	LQ2020* (Low)	LQ2020* (High)	Carbon Monitor*
R^2	-	0.74	0.54	0.93	0.79	0.65	0.84	0.88
Bias	-	10.0	11.0	-11.2	-3.4	4.0	-11.4	6.6
MAE	-	10.6	11.4	12.7	4.7	9.6	11.9	7.1
Total emission reduction relative to 2019	-11.4	-2.5 (8.9)	-1.7 (9.7)	-21.3 (-9.9)	-14.4 (-3.0)	-7.8 (3.6)	-21.5 (-10.1)	-5.5 (5.9)
Mean emission reduction during Apr & May	-23.8	-11.2 (12.6)	-23.7 (0.1)	-43.4 (-19.6)	-31.7 (-7.9)	-25.6 (-1.8)	-37.8 (-14.0)	-14.7 (9.1)

Traffic emissions in Japan in the year 2019

We further examined errors and uncertainties in the traffic-based estimates and, more fundamentally, the basic assumption by looking at the values in 2019. Figure 2 shows our fuel-based CO_2 emission estimates for 2019. The 2019 comparison further demonstrates the challenge in the use of traffic data for estimating CO_2 emissions. As also shown in Figure 1, the traffic-based estimates are also systematically higher than the fuel-based estimates in 2019, while the seasonal patterns do have similarities in noticeable peaks, such as ones corresponding to the end of Fiscal year (March, i.e. peak season for moving), summer vacations (around July-August), and snow season (December). However, the correlation of the two are not so high. This could be attributable to the lack of the consideration of car/fuel types in the traffic-based approach, sampling bias in traffic data, and the lack of the regional specificities/differences. We see this as an error associated with the methodology. Because of the systematic bias, the emission reduction estimations solely based on the traffic-based approach, which fortunately none of the published studies attempted, could be further biased by 7.2% (18.6% emission reduction).

We also looked at the Carbon Monitor estimates, which showed a very good correlation with the traffic-based approach in 2020. In fact, the Carbon Monitor emissions in 2019 looked very different from traffic-based estimates this time. Unlike the 2020 estimates, the 2019 emission calculations in Carbon Monitor begins with annual sectoral total emissions (Liu *et al* 2020a, 2020b). In fact, their traffic emissions are scaled using a portion of the total 2019 emissions. Thus, these emissions are essentially constrained by the total and thus these emissions should be discussed separately from the 2020 estimates. Since the emissions are disaggregated from a constrained sectoral total, the better agreement with our fuel-based estimates, compared to the case in 2020, was not surprising. Emissions differences among different estimates for established countries, often including Japan, are considered to be small and should agree very well (e.g. Andres *et al* 2012).

We also revealed that the Carbon Monitor estimates do not seem to capture the emission seasonality shown by our fuel-based estimates, even without the impact of COVID-19. This could be overlooked if monthly emissions are presented as monthly total emissions (see Figure S4 in Supplement Information). In that presentation, the month-to-month emission variations are largely explained by the different numbers of the days in a month and thus it would yield a higher correlation. The overlooked emission variations were small compared to the magnitude of monthly emissions due to the use of the 2019 sectoral total emission as a constraint. However, the systematic biases at monthly levels were likely to be aliased to the daily estimates via temporal downscaling, while errors in downscaled emissions by themselves can be expected to be much larger at higher temporal frequencies.

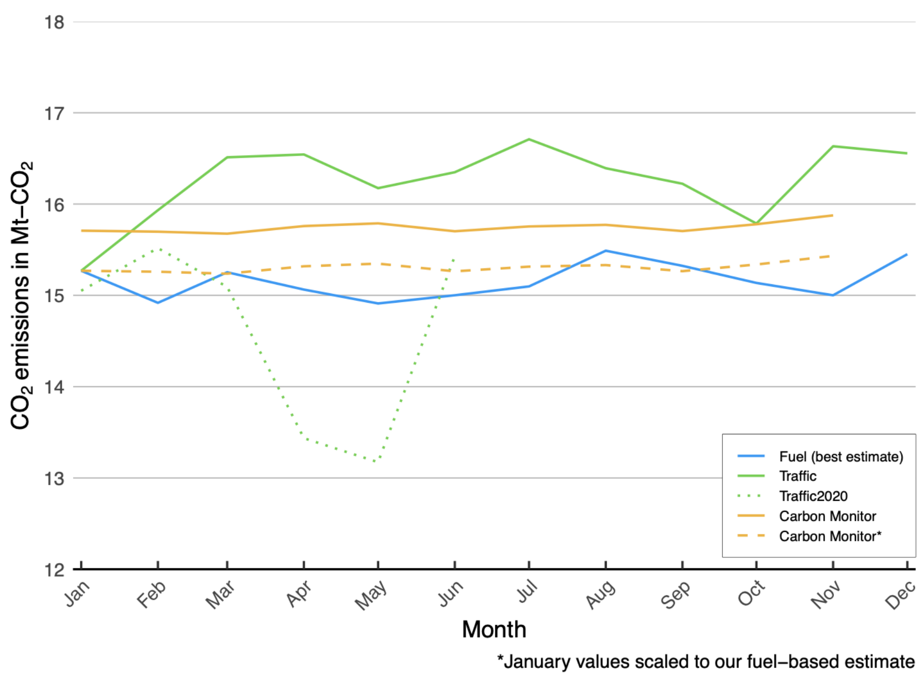

Figure 2. Monthly traffic CO_2 emission estimates in Japan for the year 2019 (non-COVID year). The blue line indicates the estimates based on monthly fuel consumption data, which should be considered to be the best estimate, and thus serve as a reference here. The green line indicates values obtained by scaling the January fuel-based estimate using monthly traffic volume changes relative to January. The yellow solid line indicates 2019 monthly estimates taken from Liu *et al* (2020b) or the Carbon Monitor (https://carbonmonitor.org/). Unlike their 2020 estimates, their 2019 estimates are based on the disaggregation of an annual sectoral estimate. The yellow dashed line indicates values obtained by scaling the Carbon Monitor estimates using the January fuel-based estimates in order to focus on the month-to-month emission variations from different estimates. Values are given in the unit of $MtCO_2$/month. To eliminate the impact of the days in a month, emission values are expressed as $MtCO_2$/30days. The monthly total emission values are shown in Figure S4 and also listed in Table S3 (the year 2020 emission values are in Table S2).

4 Discussion

This study only looked at the traffic emissions for Japan, which is the fifth-largest emitting country in the world (3.2% of the world total in 2018 by IEA (2020)). The 2018 emission share of the road transport sector (IPCC sector code: 1A3b) was 17.0% (GIO and MOE 2020), which is less dominant compared to the energy industries sector (1A1, 43.9%) and the manufacturing industries and construction sector (1A2, 24.4%). However, given the fact that traffic emissions in the recent studies are modeled systematically in a sort of generic way for most of the countries, the traffic emission estimates for other countries could be biased in the same or similar way as shown in this study for Japan. A similar error/assessment to emission estimates for other countries needs to be done in order to ensure the reasonable performance of the UAD-based emission estimation.

The successful use of UAD might open up a path for expanding our ability to model human activities and the impact on the environment. Such ability would be critical for emission monitoring towards the Paris Agreement goal beyond the COVID-19 analysis. However, our results highlight the challenges and difficulties in the use of non-science data, and the importance of thorough error and uncertainty assessment. In general, the evaluation of the performance of UAD could be extremely challenging. In addition, the lack of details further prevents us from examining and understanding the non-scientific data, as the data tech companies collect also needs to be protected in a proper way. This challenge remains even though companies might be able to bring in more data to mitigate the errors associated with spatial and temporal representation.

Nevertheless, we should keep exploring the use of UAD with the hope of providing more accurate near-real-time estimates. In fact, we mostly repurpose non-science data that are collected for some other purpose for emission calculation. We have dealt with such types of data and accumulated the knowledge. That is where the IPCC guideline comes in. While the IPCC's original scope was annual country GHG estimates, the good practice guidance can still provide a good set of guidelines to allow us to develop emission estimations. The identification of errors seems to be one of the key steps suggested by the IPCC in the use of UAD. As mentioned earlier, since the new UAD approaches do not share the basic assumptions for the emission estimation with common estimates, it is critical to examine those sources of uncertainties and reduce or mitigate them to make the final estimates as error/uncertainty free as possible.

The limitations actually further highlight the importance of the use of atmospheric observation data for evaluating emission information. Our comparison-based emission information evaluation is likely not applicable, mainly due to the lack of data at subnational levels and beyond monthly levels. In fact, several studies have included the recent near-real time emission estimates in model simulations and examine the impact of the emission changes using atmospheric observations (e.g. Keller *et al* 2020, Weir *et al* 2020, Zeng *et al* 2020). The use of atmospheric observations also allows us to detect systematic biases and possibly assure the accuracy of emission estimates, which is more critical under the Paris Agreement timeline (e.g. Oda *et al* 2019). The importance of the use of atmospheric observations in support of the successful implementation of UNFCCC has been further recognized over the recent years (e.g. IPCC 2019; Matsunaga and Maksyutov 2018). While UAD seems to be good at the timing of changes, the systematic biases are problematic. Such biases will be aliased into subsequent analyses and could hamper the assessment of climate mitigation efforts.

5 Conclusion

This study provides estimates of the impact of the COVID-19 pandemic on CO_2 emissions from traffic in Japan. Our estimates, which are based on a formal inventory calculation approach, show that the traffic emission in Japan during Japan's state of emergency (April-May) was reduced by 23.8% compared to the emission level in the previous year, despite Japan's soft approach in response to COVID-19.

We also evaluated potential errors of the UAD used in the recent estimates. We found that the basic assumption made in the recent studies, which is that traffic emissions are proportional to changes in traffic (or proxy for traffic), is not supported well-enough to provide emission estimates with an adequate level of accuracy for use in subsequent research analyses and/or policy implication. The performance of the activity data as a proxy for traffic was not sufficient, and thus is the significant source of biases and uncertainties in the recent emission estimates. More fundamentally, the relative traffic volume change does not explain seasonal emission changes, even without the impact of COVID-19. Our comparison highlighted the challenges and difficulties in use of limited UAD for modeling human activities and their impact on the environment beyond the COVID-19 emission impact analysis.

The successful use of UAD might open up a path for expanding our ability to model human activities and estimate the resulting emissions beyond the conventional annual country scale. The established IPCC guideline seems to be able to keep providing guidance on the compilation of the emissions even beyond its original scope. It is worth noting that following the IPCC guideline does not automatically support the validity and/or accuracy of the reported emission information. The establishment of the methods should involve careful QA/QC and uncertainty analysis, as suggested by the IPCC guideline. This study provided a set of evaluations, such as QA/QC and uncertainty assessment activities, that are expected to be done in the IPCC-compliant emission development process. While this study can contribute to achieving better emission estimates, the implementation of QA/QC and uncertainty assessment activities still does not fully assure the accuracy of the reported emission information. That also suggests that the importance of the use of atmospheric measurements will be important to assure the sufficient accuracy of the reported emission estimates, especially at spatial and temporal scales where no data for evaluation are available.

We plan to continue to update our traffic emission estimates and assess the impact of COVID-19 on human emissions. We also plan to expand our emission estimation and analysis to other economic sectors, with a focus on the impact of the second state of emergency just announced early this year (2021). In our future work, we will explore better ways to use the UAD to inform emissions changes in responses to human activity changes beyond national scale and possibly at human scales.

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Authors' contribution

TO designed the study. TO, CH, KH and TM conducted data collection and analysis. RB provided critical input to the error and uncertainty analysis. TO wrote the manuscript based on input from all the authors. All authors read and approved the final manuscript.

Availability of data and materials

Data used in this study, including emission estimates are presented in the main body of this manuscript and/or the Supplemental Information. All the data sources are also described. Further information can be available from the authors upon reasonable request.

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Supplement Information

Table S1. Emission factors (EFs) used in the CO_2 calculation in this study. The country-specific EFs for gasoline, diesel, Liquified Propane Gas (LPG), and Liquified Natural Gas (LNG) are taken from the version 1 of the GHG total emission calculation guideline (*in Japanese*) published by the Ministry of the Environment (MOE) Japan (see Table 5, https://www.env.go.jp/policy/local_keikaku/data/guideline.pdf, last access: 2nd February, 2020).

Fuel type	Gasoline	Diesel	LPG	LNG
Emission factor (EF)	2.32 kg-CO_2/L	2.58 kg-CO_2/L	3.00 kg-CO_2/kg	2.16 kg-CO_2/m^3

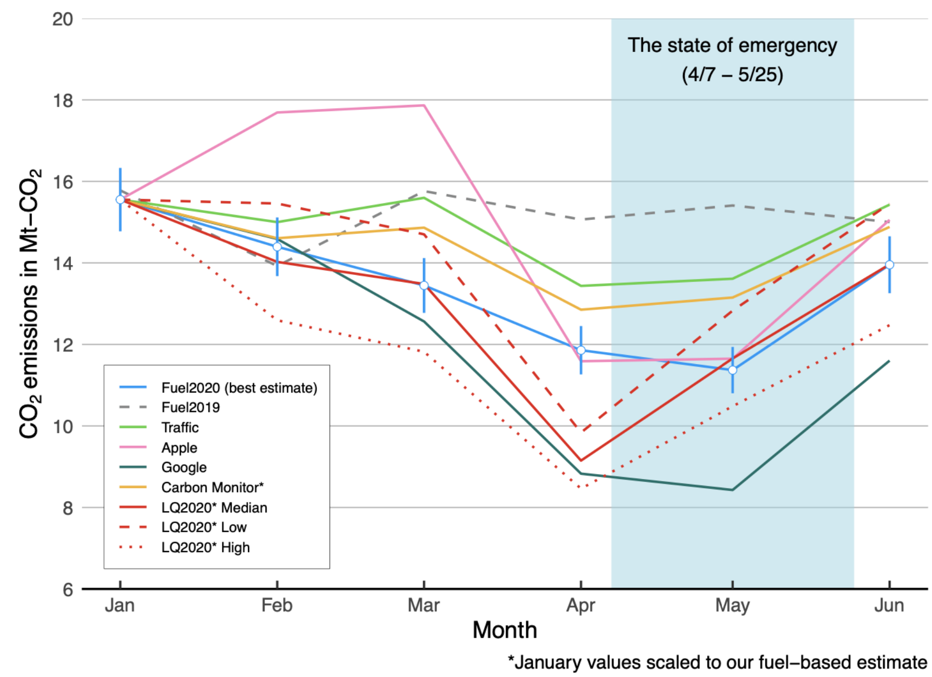

Figure S1. The same as Figure 1 in the main text, except the values are not adjusted by the number of the days in a month. The month-to-month variations shown in the figure include changes/differences due to the difference in the number of the days in a month.

Table S2. The 2020 emission values used in this study, statistics and metrics calculated. Monthly emissions are given in the unit of $MtCO_2$/month. The monthly values listed here are total monthly emissions, and are not adjusted by the numbers of days in a month. The bias/difference values are given in %. Mean Absolute Error (MAE) values are given in %. Values in the R^2 w fuel row are correlation values with fuel-based emission estimates (this study), which should serve as a measure of the accuracy of other estimates. Values in the R^2 w traffic row are correlation values calculated with traffic-based emission estimates, which should provide a measure for the UAD performance as a proxy for traffic.

	Fuel-based estimates		UAD-based estimates			Near-real time estimates			
	Fuel 2020	Fuel 2019	Traffic	Apple	Google	LQ2020* (Median)	LQ2020* (Low)	LQ2020* (High)	Carbon Monitor*
Jan	15.55	15.78	15.55	15.55	15.55	15.55	15.55	15.55	15.55
Feb	14.4	13.92	15.00	17.69	14.59	14.02	15.46	12.59	14.61
Mar	13.45	15.76	15.60	17.86	12.56	13.48	14.7	11.82	14.86
Apr	11.86	15.06	13.44	11.59	8.83	9.15	9.84	8.46	12.85

May	11.37	15.41	13.61	11.65	8.43	11.66	12.83	10.48	13.15
Jun	13.95	15.00	15.43	15.06	11.6	13.96	15.45	12.47	14.88
Sum	80.58	90.93	88.63	89.4	71.56	77.82	83.83	71.37	85.9
Total % diff. from Fuel 2020	-	12.9	10.0	11.0	-11.2	-3.4	4.0	-11.4	6.6
MAE w/ Fuel 2020	-	15.3	10.6	11.4	12.7	4.7	9.6	11.9	7.1
R^2 w/ Fuel 2020	-	0.003	0.74	0.54	0.93	0.79	0.65	0.84	0.88
R^2 w/ Traffic	0.74	0.02	-	0.75	0.68	0.80	0.79	0.67	0.95
MAE w/ Fuel 2019	12.3	-	5.9	14.9	22.6	14.5	12.3	21.4	7.0

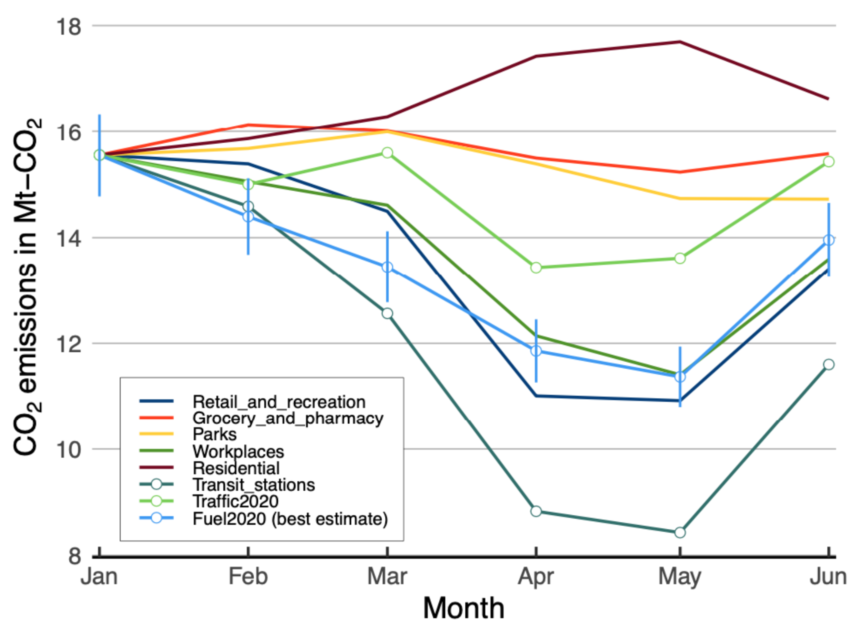

Figure S2. Monthly values obtained using six activity categories indicated in the Google Mobility Reports (Google LLC, 2021). Dark green with circles indicates the values based on the transit stations values, which is shown in Figure 1. Our best estimate (fuel-based) for the 2020 (solid blue line with circles) and the traffic-based emission values (solid light green with circles) are also shown for comparison along with five other Google categories.

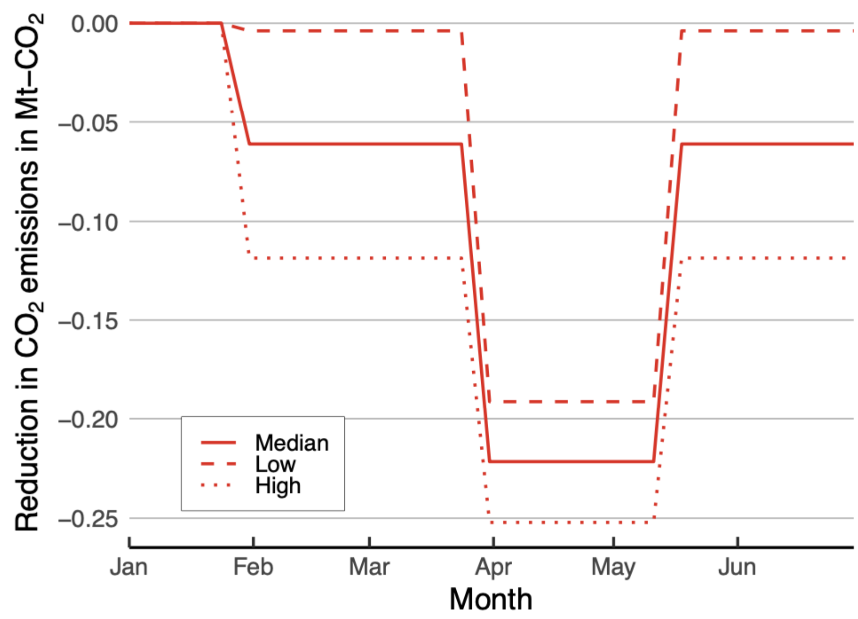

Figure S3. Daily near-real estimates for Japan, as calculated by Le Quéré *et al* (2020a). The solid line shows the median values, and the dashed and dotted lines show the high case and low case respectively. Emission values have been updated, and thus values used here might not be exactly the same as ones published in Le Quéré *et al* (2020a). Emission estimates were obtained from the Integrated Carbon Observation System (ICOS) website (https://www.icos-cp.eu/gcp-covid19, Le Quéré *et al* 2020b) (last access: 6th of January 2021).

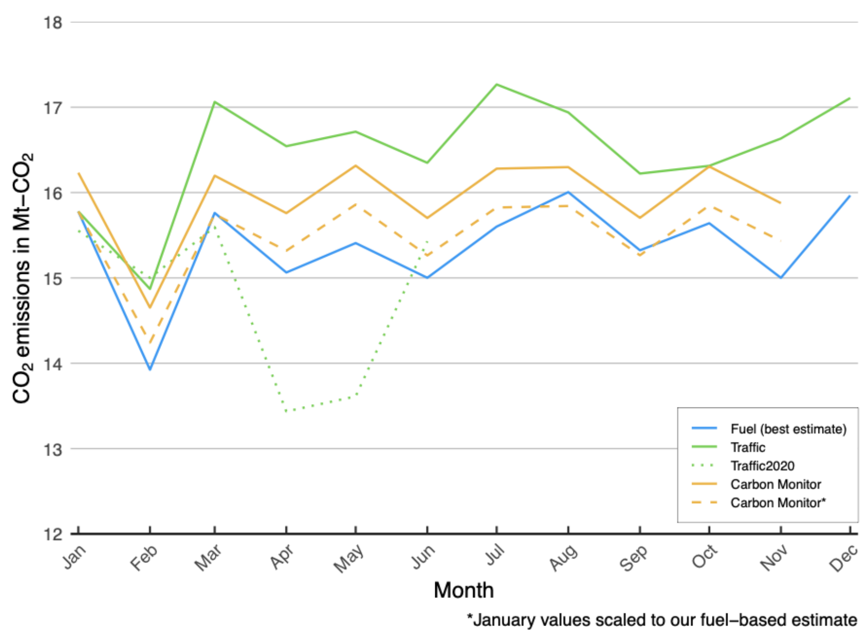

Figure S4. The same as figure 2 in the main text, excepting the values are not seasonally adjudged. The month-to-month variations shown in the figure include changes due to the number of days in a month (i.e. January has more days than February).

Table S3. The 2019 emission values used in Figure S4. Values are given in the unit of $MtCO_2$. These values are the monthly total emissions. Values are not adjusted by the number of days in a month. The month-to-month differences are thus largely explained by the numbers of days in a month, as also seen in Figure S4. Note the sums for the Carbon Monitor and the adjusted Carbon Monitor (Carbon Monitor*) are the sum of 11 months.

	Fuel	Traffic	Carbon Monitor	Carbon Monitor*
Jan	15.78	15.78	16.23	15.78
Feb	13.92	14.87	14.65	14.24
Mar	15.76	17.06	16.20	15.75
Apr	15.06	16.54	15.76	15.32
May	15.41	16.71	16.32	15.86
Jun	15.00	16.35	15.70	15.26
Jul	15.60	17.27	16.28	15.83
Aug	16.01	16.94	16.30	15.84
Sep	15.32	16.22	15.70	15.27
Oct	15.64	16.31	16.31	15.85
Nov	15.00	16.63	15.88	15.43
Dec	15.97	17.11	-	-
Sum	184.47	197.80	175.32	170.42

Table S4. Some statistics calculated from different 2019 emission estimates/values. December values for the Fuel and Traffic cases were excluded in the calculation of the metrics listed in the table. The 11 months total emissions are given in the unit of $MtCO_2$. The annual bias (Bias) and Mean Absolute Error (MAE) values are given in %. The values shown in the R^2* row are the values calculated after the number of days was adjusted to 30 days (which are shown in Figure 2 in the main text).

	Fuel	Traffic	Carbon Monitor	Carbon Monitor*
11 mon. total	168.51	181.69	175.32	170.42

Bias in %	-	7.2	4.0	1.1
MAE in %	-	7.3	4.1	1.4
R^2	-	0.53	0.88	0.88
$R^{2}*$	-	0.0006	0.05	0.05