Errors and uncertainties associated with the use of unconventional activity data for estimating CO₂ emissions: the case for traffic emissions in Japan

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Keywords: CO₂, fossil fuel CO₂ emission, COVID-19, IPCC, emission inventory, activity data

Abstract
CO₂ emissions from fossil fuel combustion (FFCO2) are conventionally estimated from fuel used (as activity data (AD)) and CO₂ emissions factor. 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 the assumed proportional relationship between traffic changes and CO₂ emissions was not enough for estimating emissions with accuracy, and moreover, the traffic-based approach failed to capture emission seasonality. Our study highlighted the challenges and difficulties in repurposing data, especially ones with limited traceability/reproducibility, 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.

1. Introduction
Carbon dioxide (CO₂) emissions from fossil fuel combustion (FFCO2) are the main drivers of the observed atmospheric CO₂ growth (e.g. Prentice 2001). Since the time of the industrial revolution, human beings have added 400 trillion metric tons of CO₂ 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 °C temperature goal and aims to achieve the goal by the mid 21st century, which requires significantly reducing greenhouse gas (GHG) emissions, including CO₂ 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 subnational contributions to the climate actions. Quantifying emissions at subnational levels, which is beyond the scope of the current Intergovernmental Panel on Climate Change (IPCC) inventory system, is thus a critical central skill for assessing and monitoring the emission reduction effort towards the Paris Agreement goal.

Conventionally, FFCO2 are often estimated using fuel statistics (e.g. Marland and Rotty 1984, IPCC 2006, Andres et al 2011, 2012). According to the emission compilation guidelines defined by the 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):

\[
\text{Emission} = \text{AD} \times \text{EF}
\]  

(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 CO₂ 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 EF. In this way (defined as reference approach in the IPCC guidelines), 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 guidelines suggests using 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. Forster et al 2020, Le Quéré et al 2020a, 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, these 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 CO₂ 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. Weir et al 2020, Zeng 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 equation (1), the use of unconventional activity data (UAD) and the emission information it aims to provide is beyond the scope of the IPCC guidelines (annual country scale). Thus, the use of UAD should have been carefully evaluated, as suggested by the IPCC good practice guidelines, 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 guidelines set 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 CO₂ 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 April–27 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 guidelines. We also examine the use of UAD for estimating CO₂ 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 CO₂ 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 CO₂ 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\textsubscript{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, and liquified natural gas. The automobile road transport emissions accounts for approximately 90% of the total transportation sector (IPCC sector code: 1A3) emissions in Japan (GOI and MOE 2020).

Following the IPCC guidelines (IPCC 2006), we calculated monthly traffic CO\textsubscript{2} emissions as follows:

\[
\text{Emission} = \sum_a [\text{Fuel}_a \times \text{EF}_a] \tag{2}
\]

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 (available online at stacks.iop.org/ERL/16/084058/mmedia)). 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. UAD-based emission calculation
While the usage of the UAD in the recent studies, such as Le Quéré \textit{et al} (2020) and Liu \textit{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:

\[
\text{Emission (t)} = \text{UAD (t)} \times E_{\text{ref}}. \tag{3}
\]

The emissions in the recent studies are estimated by scaling the reference (or baseline) emission \((E_{\text{ref}})\) 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 equation \(3\). We collected two UAD that have been used in the previous publications (e.g. Forster \textit{et al} 2020, Le Quéré \textit{et al} 2020a), 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 3 January to 6 February 2020 (5 week period). The mobility trends are reported for six categories, such as grocery and pharmacy, parks, transit stations, retail and recreation, residential, and workplaces. Following Forster \textit{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 \textit{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 18 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: (a) to evaluate the performance of Apple and Google data as a proxy for traffic count and (b) examine the performance of traffic data as an estimator of CO\textsubscript{2} emissions (see section 2.3).

We also collected the recent near-real time estimates made by Le Quéré \textit{et al} (2020a) and Liu \textit{et al} (2020a) and included them in the emission comparison/evaluation in this study. The recent studies established a relationship between Apple Mobility data and/or TomTom data and traffic emissions, and estimated daily emissions in 2020. In this study, the original daily values were aggregated to monthly levels, and scaled using our fuel-based
January value in order to focus on emission relative changes. Le Quéré et al (2020a) included the international shipping emissions in their ‘surface transport’ sector. However, since the international shipping emissions are only a few percent of Japan’s national total emissions, the relative changes should be largely driven by emissions from traffic. A summary of emission estimates compared in this study is shown in table 1.

### Table 1. A summary of the emission estimates compared in figure 1. All the estimates share the January total emission, and thus the differences among estimates are largely attributable to the performance of UAD.

| Description                                                                 |
|----------------------------------------------------------------------------|
| Fuel 2020                     | Monthly traffic emissions based on a formal inventory calculation using fuel consumption data. Used as truth in the emissions comparison for evaluating monthly relative emission changes due to different UAD approaches. |
| Fuel 2019                     | Same as Fuel 2020, but for 2019. Used as a reference to assess the relative emission reduction in 2020. |
| Traffic                       | Based on traffic count data. Monthly values were obtained by multiplying monthly relative changes to the fuel-based (Fuel 2020) January value. |
| Apple                         | Based on relative activity changes (driving) from the Apple Mobility Trends Reports. |
| Google                        | Based on relative activity changes (transit stations) from the Google Community Mobility Reports. Versions with other activity categories are shown in figure S2. |
| Carbon Monitor*               | Based on the TomTom congestion index data. An empirical emission model was constructed using hourly TomTom data and daily mean vehicle counts collected in Paris, France. In the comparison, daily emission values were aggregated to monthly levels, and then the monthly values were scaled using the fuel-based (Fuel 2020) January value in order to focus on the relative emission changes. See full details in Liu et al (2020b). |
| LQ2020*                      | Based on the Apple Mobility Trends Reports, the TomTom data, and the Confinement Index (CI). CI indicates the level of confinement, and emission changes associated with CI were based on changes indicated by activity data. The emission estimates were presented with three cases (median, high, and low). As done for Carbon Monitor estimates, the monthly values were scaled. See full details in Le Quéré et al (2020a). |

2.3. Error and uncertainty assessment
The percent uncertainty $U$ associated with the emission estimate from equation (1) can be calculated as

$$U = \sqrt{U_{AD}^2 + U_{EF}^2}$$  \hspace{1cm} (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% (2σ).

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

$$U = \sqrt{U_{UAD}^2 + U_{Ref}^2}$$  \hspace{1cm} (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 section 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 equation (3) is often subject to systematic errors due to revisions to the underlying statistical data (Andres et al 2014, Marland et al 2009) 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 also identify uncertainties that are not captured in equation (5), namely uncertainties associated with the emission calculation (or model). Such uncertainties include (a) conceptualization uncertainty and (b) model uncertainty (IPCC 2006). Following the suggestions from the IPCC guidelines, 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 guidelines as a good practice (IPCC 2006). The IPCC guidelines suggest 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

3.1. 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 2. 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 (7 April–6 May, and then extended to 27 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 Minister 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 Minister 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. Feder 2020, Gordon 2020, Nishimura 2020, Normile 2020, Wingfield-Hayes 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 2 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 section 2, 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 2). For example, the traffic count data and Apple data seem to be systematically overestimating the emissions in comparison to our fuel-based estimates. 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...
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 (7 April–25 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$_2$/30 days, 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.

have returned to normal level by the reference day for the Apple (13 January). Also, as noted by Apple Inc. (2021), the relative volume increase since 13 January 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 over-estimation 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 monthly changes from the Google data are 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. The Google-based emission monthly changes also 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.

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 using UAD as a proxy, and the need for performance evaluation. 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)
Table 2. 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.

| CO$_2$ estimates                     | UAD-based estimates | Near-real time estimates |
|--------------------------------------|---------------------|--------------------------|
|                                      | Traffic  | Apple  | Google | LQ2020*  | LQ2020*  | LQ2020*  | Carbon  |
|                                      | Fuel (Ref) |        |        | (Median) | (Low)    | (High)   | 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   | −1.7   | −21.3     | −14.4    | −7.8     | −21.5    | −5.5     |
| (8.9)                                |          | (9.7)  | (−9.9) |           | (−3.0)   | (3.6)    | (−10.1)  | (5.9)    |
| Mean emission reduction during April and May | −23.8 | −11.2  | −23.7  | −43.4     | −31.7    | −25.6    | −37.8    | −14.7    |
| (12.6)                               |          | (0.1)  | (−19.6)|           | (−7.9)   | (−1.8)   | (−14.0)  | (9.1)    |
study overestimated the emission reduction by 7.9% (median case) during the period of Japan’s state of emergency. The Le Quéré et al (2020b) 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) is a step function, and the activity level changes from the Apple data were only used to determine the magnitude of the emission changes during the confinement period. The CI was defined based on the policy implemented, rather than quantitative information, and only indicates the timing, duration, and level of severeness of the confinements (Le Quéré et al 2020a). Interestingly, the Carbon Monitor emission change is in significantly good agreement with the one based on traffic ($R^2 = 0.95$), rather than with our fuel-based estimates. The emission model was constructed based on the traffic counts data collected in Paris, France (Liu et al 2020b). The model seems to be a good estimator of traffic change in Japan at the national level, but not so much as we had hoped for CO$_2$ emissions.

3.2. 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 the monthly temporal scale 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.

4. Discussion

This study only looked at the traffic emissions for Japan. However, we believe that our results also suggested potential biases in traffic emissions for other countries, while the degree of the biases could vary. Traffic emissions in the recent studies are modeled systematically in a sort of generic way for most of the countries, and thus the issue of the performance of UAD, as well as the system boundary and spatial and temporal representativeness of UAD, is highly relevant. A similar error/uncertainty assessment to emission estimates for other countries needs to be done in order to ensure the reasonable performance of the UAD-based emission estimation. Recently, Gensheimer et al (2020) also examined the performance of UADs for estimating traffic emission changes at city levels. The same argument can also be applied to non-traffic sectors if their estimates are calculated using UAD, as discussed in the method section. The 2018 emission share of the road transport sector (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%). Thus, additional assessments will be needed to evaluate country total emissions from previous studies. Such comprehensive error/uncertainty assessments will be eventually possible when fuel-based sectorally disaggregated AD become available for many countries.

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 repurposing data, especially the ones with limited reproducibility(traceability, 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 repurposed data, as the tech companies also need to protect the privacy of their customers properly. 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, AD used in emission inventory compilation, including conventional AD, are often repurposed. We have dealt with such types of data and accumulated the knowledge and experience of using the repurposed data for emission calculation. That is where the IPCC guidelines come 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 further highlight the importance of the use of atmospheric observational data for evaluating emission information. Our comparison-based emission information evaluation is likely not applicable beyond subnational and monthly scales, 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. Weir et al 2020, Zeng et al 2020, Keller et al 2021).
The use of atmospheric observations also allows us to potentially examine 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 reasonably reflect 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 CO₂ emissions from traffic in Japan. Our estimates, which are based on a formal inventory calculation approach, show that the traffic emissions in Japan during Japan’s state of emergency (April–May) were reduced by 23.8% compared to the emission level of the previous year, despite Japan’s soft approach in response to COVID-19.

We also evaluated potential errors of the UAD-based emission estimates used in the recent estimates. The recent estimates assumed that traffic emissions are proportional to changes in traffic (or proxy for traffic). We found that the basic assumption might not be adequately supported to provide emission estimates with sufficient accuracy for use in subsequent research analyses and/or policy application. The performance of the AD 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 when using 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 guidelines are seemingly able to keep providing guidance on the compilation of the emissions even beyond its original scope. It is worth noting that following the IPCC guidelines 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 guidelines. 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 use of atmospheric observations 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.

Data availability statement

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

Acknowledgments

The authors would like to thank Apple Inc. and Google LLC for providing the mobility data that are truly valuable and insightful to the community at large. Traffic count data are collected by Japan’s National Police Agency, and provided through the Japan Road Traffic Information Center (JARTIC, www.jartic.or.jp/). The authors would like to thank JARTIC for providing us the guidance on the data use. The automobile monthly fuel consumption data are collected and provided by the Ministry of Land, Infrastructure, Transport and Tourism (MLIT, www.mlit.go.jp/k-toukei/nenryousyouhiryou.html). The near real time CO₂ estimates are hosted and provided by the Carbon Monitor website (https://carbonmonitor.org/) and the Integrated Carbon Observation System (ICOS) website (www.icos-cp.eu/gcp-covid19). The authors would like to thank David Baker, David Carlson, and Gregg Marland for their comments on this manuscript. TO is supported by NASA grants (NNX14AM76G).

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.
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