What are different measures of mobility changes telling us about emissions during the COVID-19 pandemic?

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Key Points:

- We observe differences in excess of 50% when comparing mobility datasets with traffic data from local governments.
- These differences are driven by both referencing and representation errors.
- We could not find a simple functional relationship between the mobility and traffic data, which may confound source attribution efforts.

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Abstract

The COVID-19 pandemic led to widespread reductions in mobility and induced observable changes in the atmosphere. Recent studies have employed novel mobility datasets and some used their covariations with changes in the atmosphere for source attribution. Despite their widespread use, there has been little work evaluating these mobility datasets. Here we compare mobility data from Apple and TomTom with local government traffic data in seven regions. We identify two sources of error: 1) the weekly and annual traffic cycle may not be properly represented due to the improper choice of baseline and 2) the mobility datasets are measuring fundamentally different quantities than traffic flow. We could not find a simple functional relationship between mobility data and traffic flow. Source attribution based on mobility data could induce errors in excess of 50%. Future work should be cautious when using these mobility metrics for source attribution.

Plain Language Summary

The government-imposed mobility restrictions due to the COVID-19 global pandemic led to observable changes in our atmosphere. Previous studies investigating these observed changes have used new datasets from tech companies that track users mobility. However, our work identifies important errors or shortcomings when using these new mobility datasets to directly estimate emissions from traffic. We show how there could be errors larger than 50%. Further, we could not find a simple functional relationship between these new mobility datasets and data from local governments on traffic flow, implying caution when using these mobility metrics.

1 Introduction

The COVID-19 pandemic induced widespread changes in society, impacted the global economy, and has indirectly impacted the environment. Specifically, the emergence of COVID-19 led to government restrictions on mobility including shelter-in-place orders and bans on social events (World Health Organisation (WHO), 2020). There has been much interest in understanding and quantifying how these regulations modulated both emissions to the atmosphere and the chemical composition of the atmosphere (e.g., Tanzer-Gruener et al., 2020; Turner et al., 2020; Dietrich et al., 2020). Recent studies have tried to quantify the impact of the enforced and voluntary restriction of human activities (travel and work related) on global greenhouse gas (GHG) emissions (Forster et al., 2020; Le Quéré et al., 2020; Liu, Ciais, Deng, Lei, et al., 2020; Liu, Ciais, Deng, Davis, et al., 2020) and air pollution (Venter et al., 2020). Many of these studies employed global mobility datasets from Apple Inc. (2020), Google LLC (2020), and TomTom International BV (2020) and concluded that decrease in mobility was one of the leading reason of decreased global GHG emissions and air pollution during COVID-19 lockdown periods.

These global mobility datasets are highly attractive as they provide a near-real time estimate of changes in human activity across nations and over time (Forster et al., 2020). However, in many cases, there is a lack of transparency about the methodology and, as such, we are left wondering how *exactly* these datasets relate to emissions (Forster et al., 2020). Further understanding of what these datasets can tell us is warranted.

Here we focus on mobility data provided by Apple and TomTom. We compare these datasets to both urban and rural traffic data from local governments. We identify cases where these datasets converge and where they diverge at weekly-to-annual timescales. Finally, we assess the potential errors of using these mobility datasets, in lieu of local data, on estimates of emissions to the atmosphere with a particular focus on CO_2.

2 Selection of regions for case studies

We selected seven regions (Oslo, Munich, San Francisco Bay Area, Los Angeles, Cape Town, Norway, California; supplement Table S1) as case studies to inter-compare the mobility datasets with data from local governments. These seven regions encompass both urban and rural regions from four countries on three different continents. They were chosen for their latitudinal coverage and availability of data from local governments on traffic. The distribution of the regions over the latitudes and the coverage of the northern and southern hemisphere enable a diverse data analysis. The seasons in the southern are inverse to the northern hemisphere. Additionally diverse seasonal climate behaviors are covered, for example while the temperature in Oslo shows a rather strong seasonality with peak to peak average monthly temperature differences of around 30^{o}C, in lower latitude regions, like San Francisco Bay Area the temperature fluctuation is only 10^{o}C in 2019 (supplement Figure S2). While Norway and California are comparable in size, the population of California is around 8 times higher than in Norway. From supplement Table S1 we see that all of these regions first enacted restrictions on the mobility of their populus between March 13 and March 26 in 2020. Los Angeles shows a similar behavior to San Francisco Bay Area. Its detailed analysis can be found in the supplement.

3 Information about investigated datasets

It is important to note that these various measures of mobility do not report the same quantity and what they report differs from the metrics that are traditionally used to estimate emissions to the atmosphere. We focus on vehicle traffic and therefore we do not investigate Google data which provides information about the stay of people at different locations, like transit stations.

The Apple Inc. (2020) mobility trends report represents the relative request volume of Apple Maps in the categories driving, walking, and public transportation globally. The baseline is the request volume as of Monday, January 13, 2020, reaching from midnight to midnight of the corresponding day in Pacific Time Zone. Apple Inc. (2020) themselves state that increases of their index can occur due to usual seasonality. Also they do not collect user or demographic information and Apple Maps is only available on Apple devices. Therefore it is unknown whether the use is representative for the entire population.

TomTom International BV (2020) traffic index provides congestion levels for 416 cities in 57 countries of the world. Due to the COVID-19 pandemic the average daily congestion for the year 2020 and also the deviation from the corresponding day in 2019 are published. The corresponding day in 2019 is defined as the same weekday of the same calender week. The percentage congestion value represents the extra time needed for a trip compared to the uncongestioned traffic situation. For example, if an uncongestioned trip takes 30 minutes and the congestion index currently is 50%, then the trip takes 15 minutes longer (50% of 30 minutes) and therefore in total 45 minutes. The traffic index is calculated with the data of more than 600 million global users who navigate with TomTom technology in navigation devices, smartphones or other technical devices. The uncongestioned situation is analyzed by looking at free-flow local traffic situations.

In contrast to mobile device based data gathering, the local governments in this study measure traffic by point counting stations using microwave radar detectors or induction loops on roads and at traffic lights. For California, we consider the vehicle miles traveled (VMT) metric (California State Senate SB 743, 2015). For all other regions we use the total average daily traffic volume of all point detectors. Data was downloaded directly from the websites or requested from the local governmental departments. For Oslo we reduce the data of whole Norway using the longitude borders (10.6678, 10.6678) and the latitude borders (59.8214, 60.0015) which represent a distance of approximately 10 kilometers from the city center. (Statens vegvesen, 2020; Bayerisches Landesamt fuer

Umwelt (LfU), 2020; Caltrans, California Department of Transportation, 2020; Western Cape Government, Road Network Information System, 2020)

4 Data analysis

Figure 1a shows the monthly deviation from the annual mean traffic flow for six of the seven study regions. We observe little seasonality in California (deviations are less than 5%, similar to McDonald et al. (2014)), in contrast to other regions. This lack of seasonality is due, in part, to the temperate climate. The European regions Munich, Oslo, and Norway show deviation peaks up to 9-12%. In Norway and Oslo a break in the curve can be observed in July which coincides with the local school summer break. Further, we observe the inverse seasons on the southern to the northern hemisphere in the annual traffic cycle when we compare Cape Town with the urban study sites Munich and Oslo. Generally the traffic is weaker in the local winter months as in the local summer months at all investigated regions. The traffic seasonality at higher latitude is larger than at lower latitude e.g. in California.

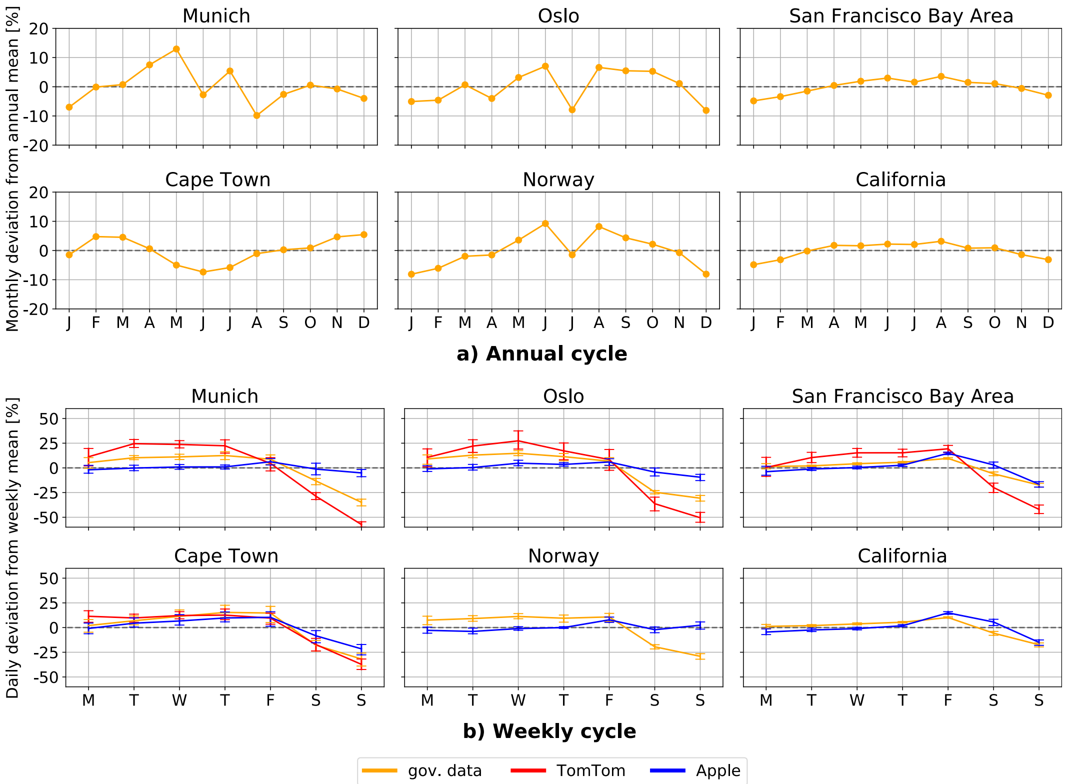

Figure 1. Annual and weekly cycle of traffic and mobility data a) Annual traffic cycle. Deviation of the mean monthly local governmental data of the corresponding month in 2019 to the mean of the year 2019. b) Weekly traffic cycle. Deviation of the daily data of the corresponding weekday to the mean of the corresponding calender week with 2σ error bars for the time span from 01/14/20 until 07/31/20.

Figure 1b shows the daily deviation in traffic flow relative to the weekly mean traffic flow for data from the local government, Apple, and TomTom. In all cases we observe a decrease in traffic flow (governmental data) and TomTom's congestion index on the weekend. Regional differences can be observed during the week. While at the locations

Munich, Oslo, and San Francisco Bay Area the TomTom data shows a bend throughout the week, in Cape Town the daily weekday congestion levels do not differ from each other. Friday shows generally the highest request volume of Apple Maps. In Munich, Oslo, and Cape Town the request volume decreases on the weekend compared to the week. In Norway the weekend request volume is similar to that during the week while in California it decreases on Sundays but is similar to the weekly mean on Saturdays.

In particular, the low traffic volume on weekends is not as noticeable in Apple's data. For the days Monday to Thursday all study regions show a higher deviation from the weekly mean for TomTom and governmental data than Apple. At all regions except for Cape Town the TomTom data is always further deviated from the weekly mean than the governmental data which indicates a non-linear relationship between the datasets.

Apple data is pegged to a Apple Maps request volume on Monday January 13, 2020. The annual traffic cycle (Fig. 1a) and the weekly traffic cycle (Fig. 1b) reveals the importance of taking traffic seasonality into account. Even if weekly deviations are minded, the annual cycle still needs to be considered. Differences in the weekly cycle could also indicate differences in the annual cycle of Apple data compared to governmental data. Unfortunately we do not have historical data for the Apple mobility index as this product was only made public in response to the COVID-19 global pandemic.

Ultimately, we are interested in knowing how these mobility datasets relate to changes in traffic and what, if any, errors would be induced by using this data as a proxy for changes in traffic. To assess this we compute the relative change since January 13, 2020 for each dataset to facilitate comparison to the Apple data. For the local governmental data and the TomTom data we also compute the deviation of each day to the same weekday of the same calender week in 2019 to investigate the impact of a chosen reference value.

Figure 2 shows a scatterplot comparison of the mobility and congestion indices against the traffic flow reported by the local government. The coloring of the dots represents the distance to the first day of governmental COVID-19 restrictions. With increasing brightness the dots are longer before the first restrictions, while with more darkness they are longer after. A few prominent features stand out such as the nonlinear correlation for TomTom in Munich, Oslo, and San Francisco Bay Area and for Apple in Munich and Norway. The correlation is rather linear for Apple and TomTom in Cape Town and only for Apple in Oslo, San Francisco Bay Area, and California. Munich (Fig. 2a) shows a complicated behavior. Traffic changes in the range of 0% to -10% can lead to TomTom's congestion and Apple's mobility value increases of up to 60%. Traffic reductions are overestimated by TomTom and down to -50% the relationship is scattered for Apple. Cape Town (Fig. 2b) shows a nearly linear relationship of traffic flow and Apple mobility changes. TomTom underestimates the traffic reduction in this case which is not observed in any other region. Oslo (Fig. 2c) does not seem to show any relationship between Apple's data and governmental data. It stands out that the TomTom data is not scattered and shows a non-linear correlation. For San Francisco Bay Area (Fig. 2d), Apple overestimates the traffic flow decline with increasing traffic reduction. The congestion change shows an interesting behavior as a traffic reduction of 10% leads to congestion reduction of 60%, while a traffic reduction of 60% results in 80% less congestion. For the rural areas we chose another y-axis limit of 200% which is due to the high increase of the Apple mobility report for Norway (Fig. 2e). For California (Fig. 2f) the Apple mobility report underestimates small traffic flow reductions down to -25% but overestimates the range of -25% to -50%.

Figure 3 shows a time series of the relative traffic flow for the study regions. Each solid line is related to January 13, 2020 and for the dashed lines each day is related to the same weekday of the same calender week in 2019. In contrast to the data in Figure 2, here a seven days rolling mean is applied to the data. All datasets show an abrupt drop in early March 2020. Interestingly, all of the regions show a nearly synchronous decline even though the actual government restrictions were implemented over a 3 week period (supplement Table S1). Hence, San Francisco Bay Area, Munich, and Cape Town show decreases prior to their actual governmental restriction. The trend of traffic flow is nearly

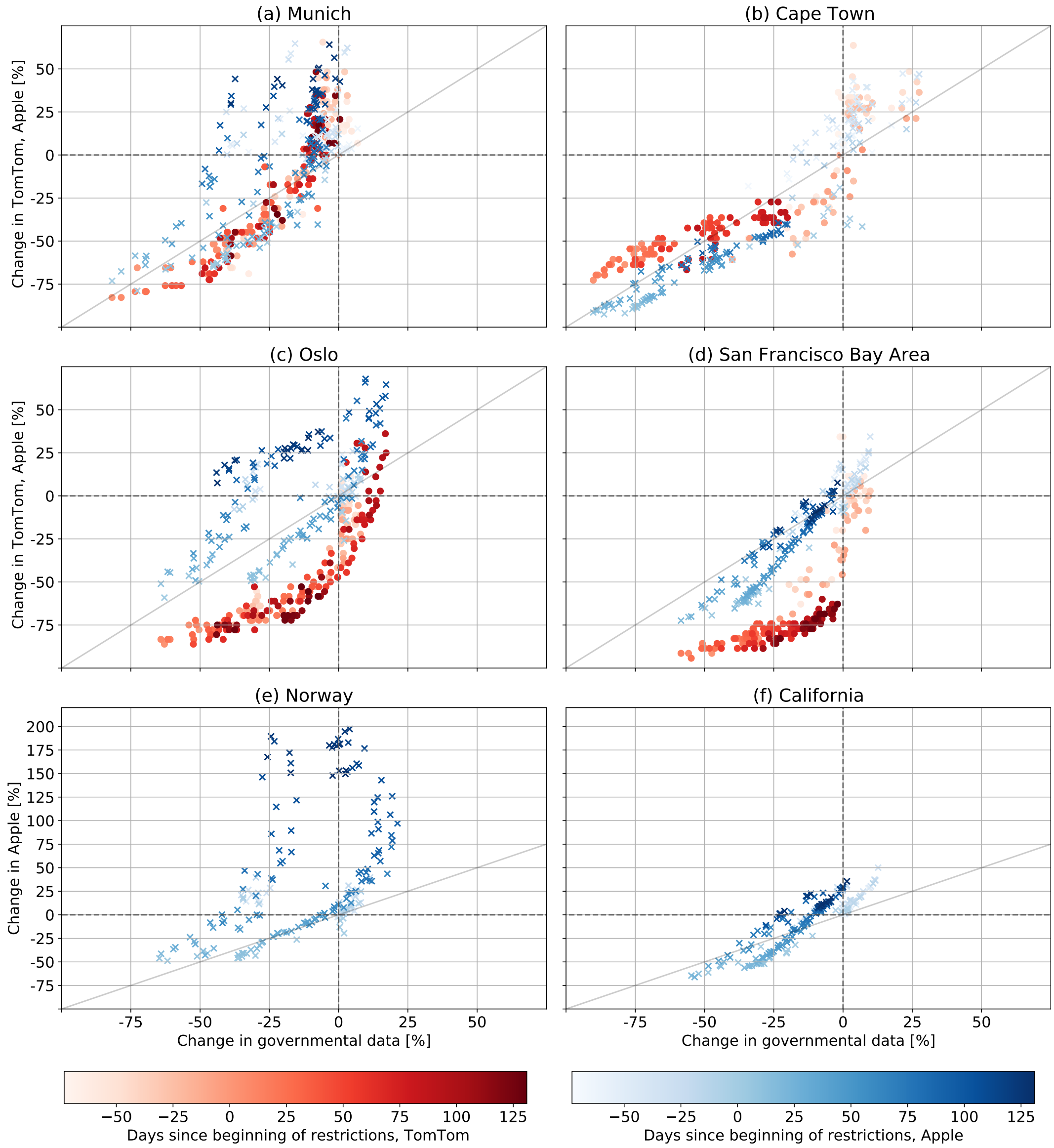

Figure 2. Comparison of different measures of traffic flow. The scatter shows the daily comparison between the governmental data to Apple's mobility data and TomTom's congestion index. All data is referred to January 13, 2020. The coloring of the dots is done by the distance to the first day of governmental COVID-19 restrictions.

independent of the reference value for Norway and California. For Munich and Oslo the reference value plays a crucial role for traffic flow. For the TomTom congestion index the reference value is important for Munich and Oslo, while the data is nearly independent from it for Cape Town and San Francisco Bay Area for the time since the first governmental restrictions.

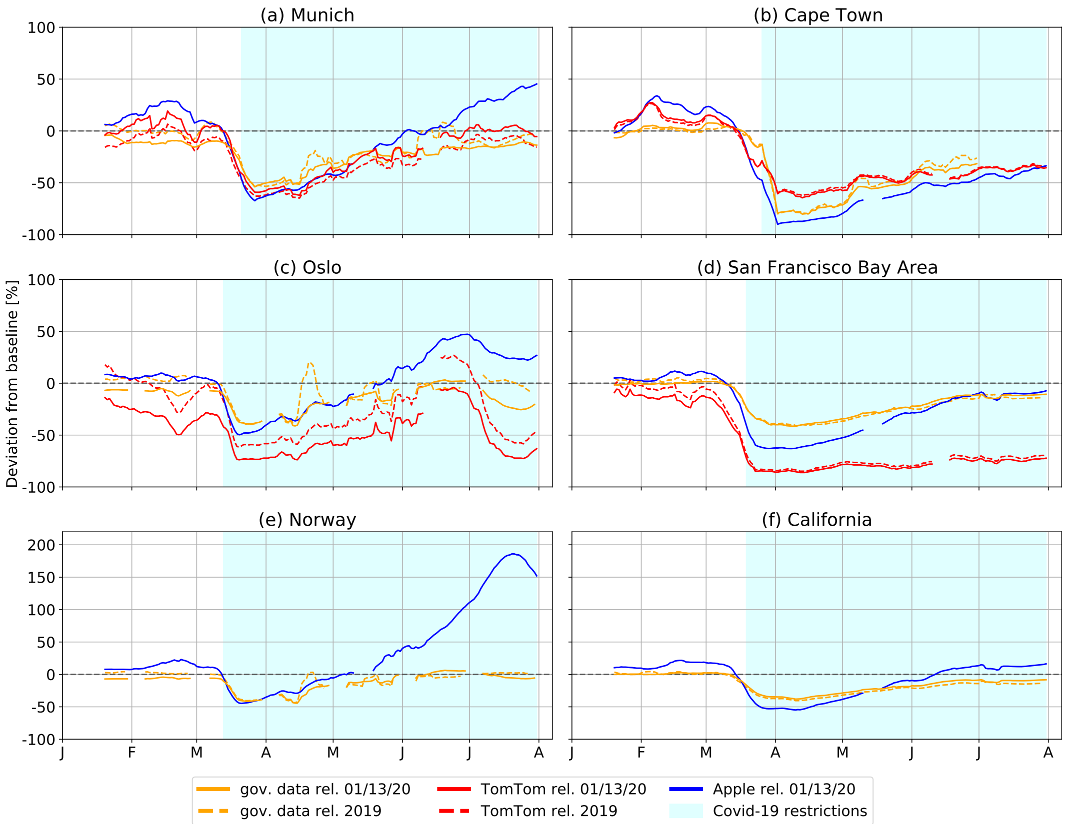

Figure 3. Time series trend comparison. Apple, TomTom, and governmental data. *rel.*2019: each day is related to the same weekday of the same calender week in 2019. *rel.*01/13/20 each day is related to the value on January 13, 2020. A 7 days rolling mean is applied to the data.

Interestingly, the annual cycle (Fig. 1a) of Oslo and Norway is similar but the deviation between traffic flow reduction related to January 13, 2020 and to 2019 differs in the two regions. The deviation between the two lines is much bigger for Oslo as for Norway. California in total shows a similar traffic flow reduction as San Francisco Bay Area. However, the reduction of Apple mobility index in California is smaller and crosses the traffic flow line in mid May. For San Francisco Bay Area the Apple mobility index shows a similar timeseries as governmental data from mid June to end of July. For the European regions Munich, Oslo, and Norway Apple increases over its reference value in mid or end of May and rises up 50% to 190% while traffic is only nearly back to its reference value or still below in end of July. This behavior indicates a high seasonality for the Apple mobility data for these regions that differs from the traffic flow seasonality.

We observe that some of the scatter in Figure 2 is due to the weekly cycle, shown in Figure 1b. Although linking it with the scatter plots for weekly means in supplement Figure S4 and the trend timeseries in Figure 3 shows that in the overall trend the differences of the dataset are not just due to the reference value.

5 Impact on interpretation of trace gas fluxes

All of this begs the question, *"What do these different measures of traffic and mobility imply about emission changes?"* We assess this by assuming the data from the local government to be most accurate and look at differences relative to these datasets. We compute the percentage emission difference of the datasets compared to the local government data and use San Francisco Bay Area as a case study to introduce an exemplary amount of trace gas differences.

Figure 4 shows the difference in trace gas emissions since January 13, 2020 until the corresponding day on the horizontal axes when TomTom's congestion index or Apple's mobility data is used as a proxy for traffic changes instead of governmental traffic data. If the deviation is negative the usage of the mobility dataset results in a lower estimated emission number as when using the local governmental data. The calculation is done by Equation 1

$$\Delta E(d, g, t) = \frac{\sum_{i=1}^{t} (d_i - g_i)}{\sum_{i=1}^{t} g_i} \tag{1}$$

where ΔE is the difference in trace gas emissions on the vertical axes in percent; t is the day on the horizontal date axes; g the local governmental data; and d the datasets of Apple or TomTom. We later use Eq. 1 with combinations of different baselines (either January 13, 2020, or the corresponding weekday of the same calendar week in 2019) for both the local government and mobility data. In Figure 4, the data are denoted as $d^{13,Jan}$, $g^{13,Jan}$, d^{2019}, and g^{2019}, depending on the baselines that are used for the referencing.

We observe that the difference between emissions estimates based on governmental traffic data to estimates based on TomTom congestion index or Apple mobility data differ at each study region and depend on the timepoint of investigation (day t after the reference day). The datasets can be a good proxy at one location at a specific time but deviate at another location at the same time (e.g. San Francisco Bay Area vs. California in end of March). The resulting emission differences caused by Apple's data are in the range of -7% to 59% and by TomTom's data in the range of -51% to 25%.

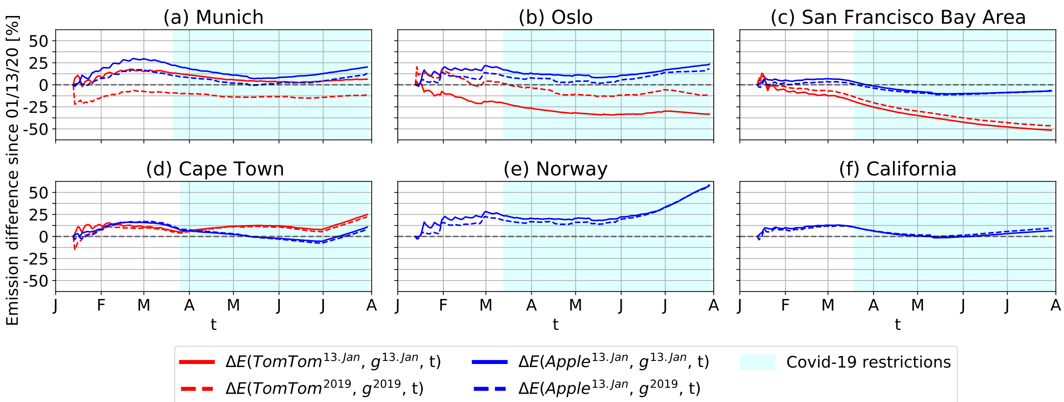

Figure 4. Timeseries of the emission difference (ΔE, Equation 1) of TomTom's and Apple's data compared to governmental data. The value assigned to one day is the difference in emission calculation for the time span from January 13, 2020 to the corresponding day t using Apple's or TomTom's data (d) instead of governmental traffic data (g) following Equation 1.

We use Caltrans, California Department of Transportation (2020) VMT measure for San Francisco Bay Area as input to the California Air Resources Board's EMFAC

(2014) model to calculate the vehicle trace gas emissions on January 13, 2020. We use the default vehicle fleet of the model for the ratio of vehicle classes. We then apply the deviations of the three datasets from January 13, 2020 to the previously calculated vehicle emissions on that day. For the period of 01/13/20 to 31/07/20 the total differences in the Bay Area when using Apple instead of VMT are for CO_2: 0.43 Mt, NO_x: 425 t, PM: 64 t which is a relative difference of -7%. Using TomTom instead of VMT results in an emission difference for CO_2: 3.1 Mt, NO_x: 3103 t, PM: 466 t (-51%). The percentage error can also be observed in Figure 4 and compared to other regions.

For many environmental models inventories of total emissions are of major interest. The Bay Area Air Quality Management District (BAAQMD) provides annual CO_2 emissions for California's Bay Area for the year 2011 (Claire et al., 2015). The transportation sector contributes to these by 39.7% of which 88.7% is caused by road vehicles. The share of road emissions in total emission is thus 35.2%. We are interested in how the mobility datasets impact the total emission estimates with the assumption that only the transportation sector is affected during COVID-19. To get an order of magnitude we assume the share of the transportation sector for the year 2011 also accounts for the time span from January 13, 2020 to July 31, 2020, knowing we are neglecting annual emission cycles and year to year emission changes. Using the Apple mobility data as a proxy for road transportation, results in an emission difference of -7% in the transportation sector, which impacts the total emission estimates by -3%. For TomTom, the error in the transportation sector is -51% and therefore changes the total emission estimates by -18%. Hence, both mobility datasets, when used as a proxy for traffic, result in a noticable - or in case of TomTom even significant - overestimate of traffic and emission reduction for the San Francisco Bay Area during the COVID-19 pandemic.

6 Discussion and conclusions

In this study, we compared widely used measures of mobility published by Apple and TomTom with high quality data from local governments to facilitate their use in COVID-19 impact studies. We identify two major error sources in using the TomTom congestion index or the Apple mobility data as a proxy for vehicle traffic:

1. **Referencing error.** The impact of the weekly and annual traffic cycle is non-trivial. Use of a fixed (arbitrary) time-point reference value may yield incorrect conclusions (see Figs 1, and 3).
2. **Representation error.** The datasets investigated here measure different quantities. Local governments typically measure traffic volume and/or vehicle miles traveled, Apple's mobility dataset is a measure of their request volume from navigation systems (Apple Maps), and TomTom's congestion index measures urban congestion levels. Even when using the same baseline the deviation of the datasets is, again, non-trivial (see Figs 2 and 3).

These error sources do not allow us to develop a generalizable relationship between mobility data and traffic flow (see Figs 2, 3, 4). They result in deviations of -7% to +59% and -51% to +25% for Apple and TomTom, respectively, in the vehicle trace gas emission estimates compared to data from the local government. These percentage values depend on the region of interest and time of investigation. In the case of the San Francisco Bay Area, using the mobility data from Apple and TomTom results in an emissions estimate for transportation that are, respectively, 0.43 Mt CO2 and 3.1 Mt CO2 lower than what government traffic data implies, resulting in total emission estimates that differ by -3% and -18%.

Despite their widespread use, there is a lack of understanding about what exactly these mobility metrics are telling us about the change in trace gas emissions due to COVID-19. Here we quantified the potential errors that might be inferred by using these mobility metrics as a proxy for changes in trace gas emissions. The findings presented here should serve to caution others from directly using these mobility measures as a proxy without additional investigation or adaptation.

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