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

Johannes Gensheimer[1], Alexander J. Turner[2,3], Ankit Shekhar[4], Adrian Wenzel[1], Frank N. Keutsch[5], and Jia Chen[1]

[1]Environmental Sensing and Modeling, Technical University of Munich (TUM), Munich, Germany
[2]Department of Atmospheric Sciences, University of Washington, Seattle, WA, 98195, USA
[3]Jet Propulsion Laboratory, California Institute of Technology, Pasadena, CA 91109, USA
[4]Department of Environmental Systems Science, ETH Zurich, 8092 Zurich, Switzerland
[5]School of Engineering and Applied Sciences and Department of Chemistry and Chemical Biology, Harvard University, Cambridge, Massachusetts, USA

Key Points:

- In light of the COVID-19 pandemic, vehicle emission reductions are in the range of 7-22% in seven investigated urban and rural regions.
- Recent work used mobility data for assessing the impact of the pandemic on traffic emissions. However, we observe errors in excess of 60%.
- Referencing and representation errors are the main drivers for the discrepancies, which can not be described by functional relationships.

Corresponding author: Johannes Gensheimer, `johannes.gensheimer@tum.de`

Corresponding author: Jia Chen, `jia.chen@tum.de`

Abstract

The COVID-19 pandemic led to widespread reductions in mobility and induced observable changes in the atmosphere. Recent work has employed novel mobility datasets as a proxy for trace gas emissions from traffic, yet there has been little work evaluating these emission numbers. Here, we systematically compare these mobility datasets to traffic data from local governments in seven diverse urban and rural regions to characterize the magnitude of errors in emissions that result from using the mobility data. We observe differences in excess of 60% between these mobility datasets and local traffic data, which result in large errors in emission estimates. We could not find a general functional relationship between mobility data and traffic flow over all regions. Future work should be cautious when using these mobility metrics for emission estimates. Further, we use the local government data to identify emission reductions from traffic in the range of 7-22% in 2020 compared to 2019.

Plain Language Summary

The government-imposed mobility restrictions due to the COVID-19 pandemic led to observable changes in our atmosphere. We identify atmospheric traffic emission reductions in the range of 7-22% in 2020 compared to 2019 in seven diverse urban and rural regions using traffic data from local governments. Previous studies investigating these observed changes used new datasets from tech companies that track user mobility. However, our work identifies important shortcomings using these new mobility datasets to directly estimate emissions from traffic, with calculated emission errors larger than 60%. 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 for assessing emissions.

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 et al., 2020) and air pollution (e.g., Venter et al., 2020; Grange 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 about trace gas emissions and atmospheric composition is warranted.

Here we investigate these measures of mobility and compare them to data from local governments regarding their utility as a proxy for trace gas emissions from traffic. Through a series of case studies in seven urban and rural regions, we highlight cases where the mobility data is consistent with local governmental data on traffic flow and, importantly, cases where the mobility data is inconsistent. We then quantify the potential errors in emission estimates when using these mobility datasets timely and regionally divided with a particular focus on CO_2. Finally, we provide an estimate of emission changes due to COVID-19 based on the available local government data for the regions analyzed in our case studies.

2 Regions for case studies and investigated datasets

We selected seven regions (Oslo, Munich, San Francisco Bay Area, Los Angeles, Cape Town, Norway, California; Supplemental Table S1) as case studies to identify the impact of COVID-19 on traffic emissions. 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 comprehensive data analysis. Diverse seasonal climate behaviors are covered, for example the strong and weak temperature seasonality in Oslo and in California (Supplemental Figure S2). While Norway and California are comparable in size, the population of California is around 8 times higher than in Norway. From Supplemental Table S1 we see that all of these regions first enacted restrictions on the mobility of their populations between March 13 and March 26 in 2020. Los Angeles shows similar effects to San Francisco Bay Area (see Supplemental Section S10).

It is important to note that the measures of mobility do not all report the same quantity. Additionally, the metric reported in the mobility datasets differs from the metrics that are traditionally used to estimate emissions to the atmosphere (e.g., Janssens-Maenhout et al., 2019; Oda et al., 2018).

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.

The 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 daily percentage congestion value for the year 2020 and also the deviation from 2019 are published. The percentage congestion value represents the extra time needed for a trip compared to the uncongested traffic situation. For example, if an uncongested trip takes 30 minutes and the congestion index currently is 50%, then the trip takes 15 minutes longer. Each weekday is related to the annual average congestion of that same weekday in 2019. 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 uncongested situation is analyzed by looking at free-flow local traffic situations.

Here we focus on vehicle traffic and therefore we do not investigate Google LLC (2020) data which provides information about the stay of people at different locations, like e.g. transit stations. As it is included in some recent studies (e.g., Forster et al., 2020; Venter et al., 2020) we have included our investigation in the supplemental material (Supplemental Section S11).

In contrast to mobile device based data gathering, the local governments 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 Norway by cropping a square with 10 km distance to the city center of Oslo. (Statens vegvesen, 2020; Bayerisches Landesamt fuer Umwelt (LfU), 2020; Caltrans, California Department of Transportation, 2020; Western Cape Government, Road Network Information System, 2020)

From Figure 1, we can see that all of the data 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 (Supplemental Table S1). Hence, the San Francisco Bay Area, Munich, and Cape Town show decreases prior to their actual governmental restriction. We identify deviations, such as the large increase in summer time in Munich, Oslo, and Norway in the Apple data when compared to governmental traffic data and TomToms congestion index. All of the regions analyzed here show substantial differences between mobility and traffic. As such, we are interested in characterizing what drives these differences and the impacts on bottom-up emissions inferred using mobility data.

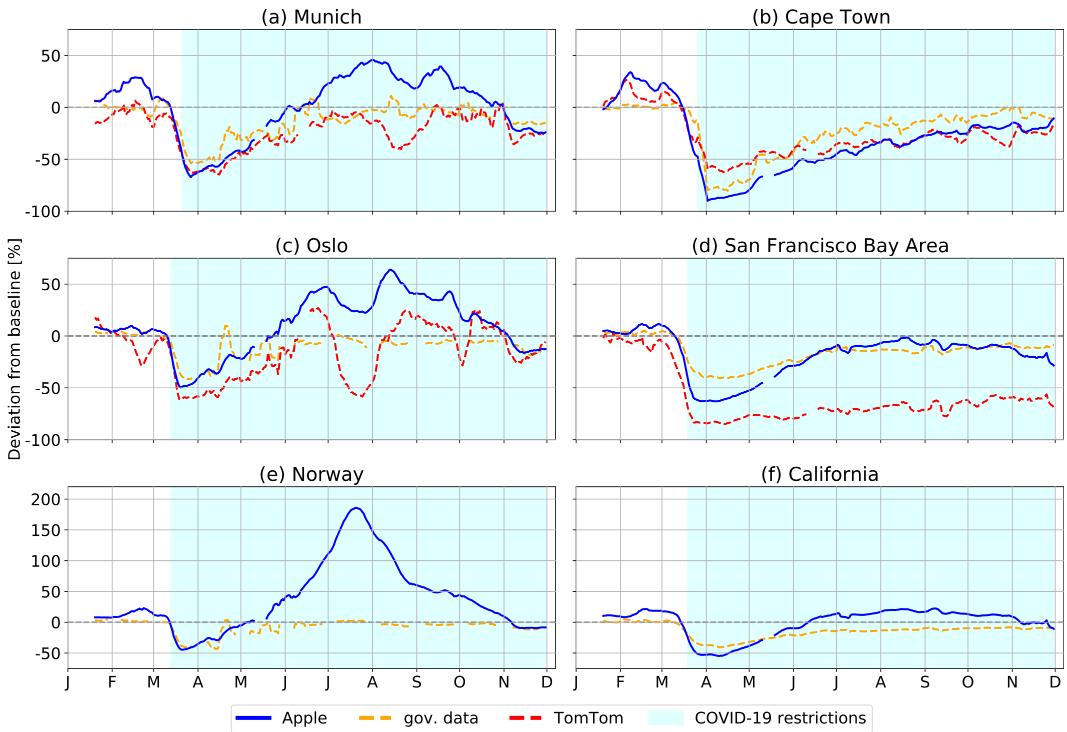

Figure 1. Time series trend comparison of different mobility and traffic datasets. Apple data is relative to its request volume on January 13, 2020. There is no 2019 data for the Apple mobility index as this product was only made public in response to the COVID-19 pandemic. The governmental traffic data each weekday is related to the same weekday of the same calendar week in 2019 and for TomTom data each weekday is related to the annual average congestion of that weekday in 2019. A seven day rolling mean is applied to the data to remove the weekly cycle.

3 Assessing differences between the datasets

As mentioned above, all regions analyzed here show sizable differences between the temporal evolution of the mobility data and local traffic data (see Figure 1). Additionally, the temporal evolution of these differences varies across regions, and not in an easily predictable manner. Nevertheless, we are interested in identifying the underly causes of these differences to establish a relationship between mobility and traffic to facilitate their use in developing bottom-up emission estimates and inferring processes driving changes in atmospheric composition.

Figure 2a shows the monthly deviation from the annual mean traffic flow for six of the seven study regions using governmental data. We observe little seasonality in California (deviations are less than 5%, similar to McDonald et al. (2014)), in contrast to other regions, which is due, in part, to the temperate climate. The European regions Munich, Oslo, and Norway show deviations peak of up to 9-12%. Further, we observe the inverse seasons in 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 than in the local summer months in all investigated regions. The traffic seasonality at higher latitude is larger than at lower latitude e.g. in California.

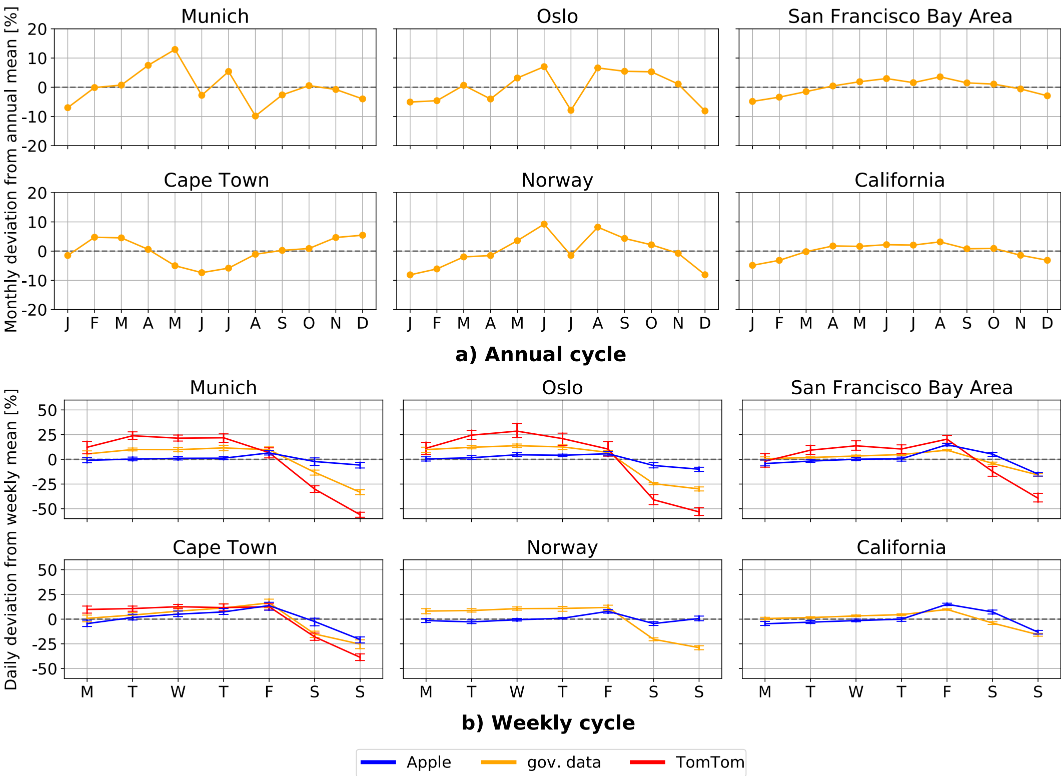

Figure 2. Annual and weekly cycle of traffic and mobility data a) Annual traffic cycle. Deviation of the mean monthly local governmental data of the corresponding month in 2019 to the mean of the year 2019. b) Weekly traffic cycle. Deviation of the daily data of the corresponding weekday to the mean of the corresponding calendar week with 2σ error bars for the time span from 01/14/20 until 11/30/20.

Figure 2b shows the daily deviation in traffic flow relative to the weekly mean traffic flow for data from the local government, Apple, and TomTom. All regions show a pronounced decrease in governmental data and TomToms congestion index on the weekend. A particularly interesting regional difference is the weekly cycle in the TomTom data for Munich with positive anomalies from Monday through Thursday and a sharp decrease from Friday through Sunday. This feature is observed in both TomTom and the local government data, but not Apple mobility data. A similar pattern is seen in Oslo and Cape Town, but is notably different than San Francisco where all datasets indicate the largest, positive, anomaly on Friday. Apple data indicates the largest positive anomaly on Fridays across all regions. The lower traffic values seen on weekends in local governmental data and TomToms congestion index is also notably smaller in the Apple Maps mobility data.

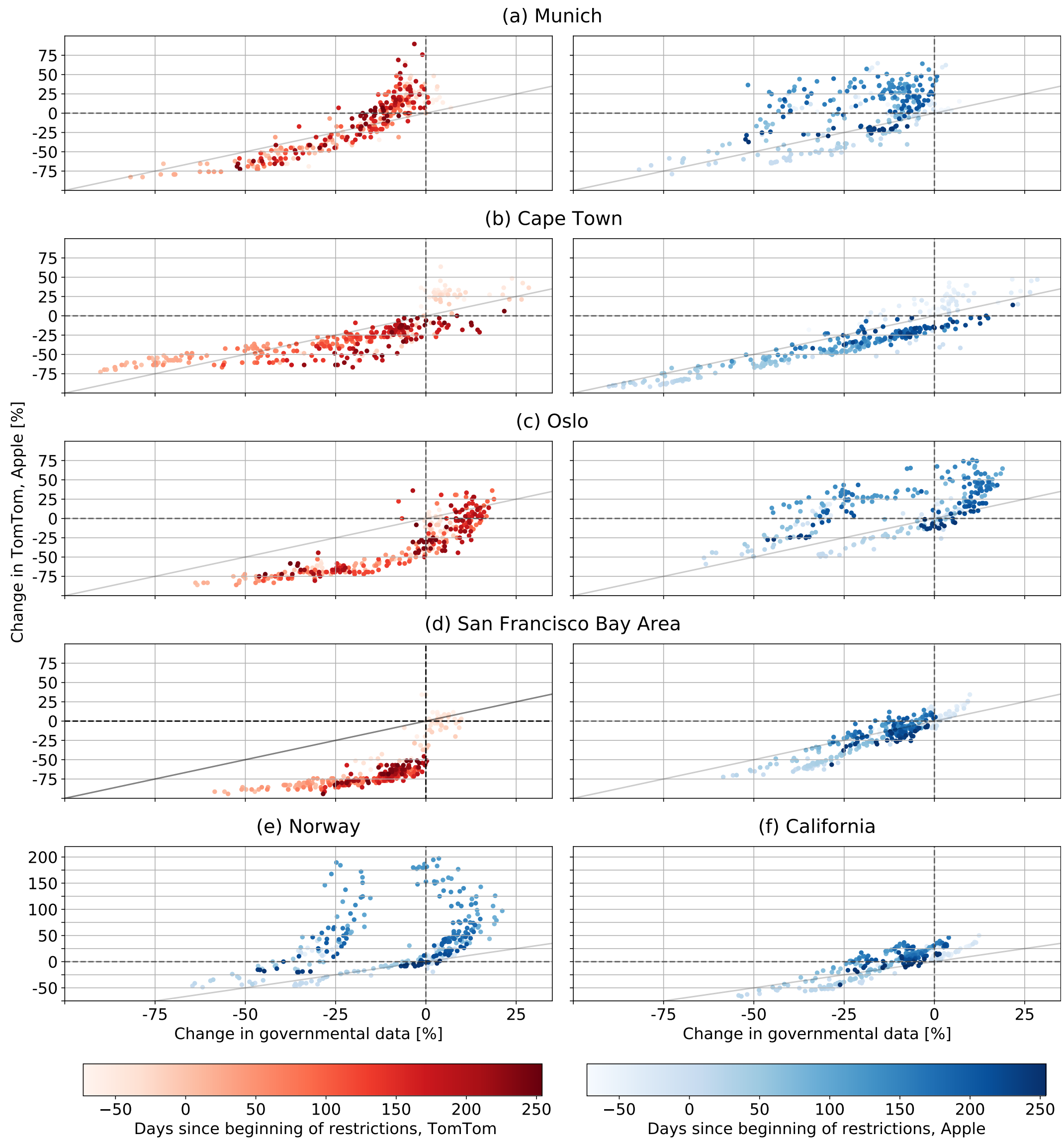

Figure 3. Comparison of different measures of traffic flow. The scatter shows the daily comparison between the governmental data to Apples mobility data and TomToms congestion index. All datasets are referred to their value on January 13, 2020. The coloring of the dots is done by the distance to the first day of local governmental COVID-19 restrictions.

The annual traffic cycle (Fig. 2a) and the weekly traffic cycle (Fig. 2b) reveals the importance of taking annual and weekly seasonality into account, which is however not the case for Apple data. TomTom data includes weekly cycles but neglects its annual cycle. Supplemental Figure S1 shows the timeseries of all datasets related to January 13, 2020. We observe large differences between datasets which reveals that the referencing issue only partially explains the differences in Figure 1. These remaining differences can be attributed to the representation discrepancies that are listed in Section 2.

We have highlighted differences between Apple mobility, TomTom congestion and governmental traffic data (Figure 1). In Figure 3 we assess the relationship between these metrics using scatterplots. We are interested in comparing the representation of these metrics and therefore we remove the different baselines by referring all datasets to their value on January 13, 2020. 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.

From Figure 3 we can see the differences between these metrics cannot be characterized by a relationship that generalizes over all regions. The relationship differs between cities and is highly scattered for some regions. Removing the impact of weekly cycles by only comparing weekly means shows a similar trend (Supplemental Figure S5). This indicates that work should be cautious when attempting to estimate trace gas emissions in response to COVID-19 using (scaled) mobility data, as a number of recent studies have done (e.g., Forster et al., 2020; Le Quéré et al., 2020; Liu et al., 2020). In supplemental Figure S15 we have applied the functional relationship of Liu et al. (2020) to the TomTom congestion index in our study regions and observe big regional differences to real governmental traffic data.

4 Impact of mobility datasets on estimated atmospheric emission change

We identify that different measures of traffic and mobility that are currently used for bottom-up emission estimates deviate strongly from each other. This begs the question, *"What do these different measures of traffic and mobility imply about emission changes?"*. We assess this by assuming that the data from the local governments is the most accurate and look at differences relative to these datasets.

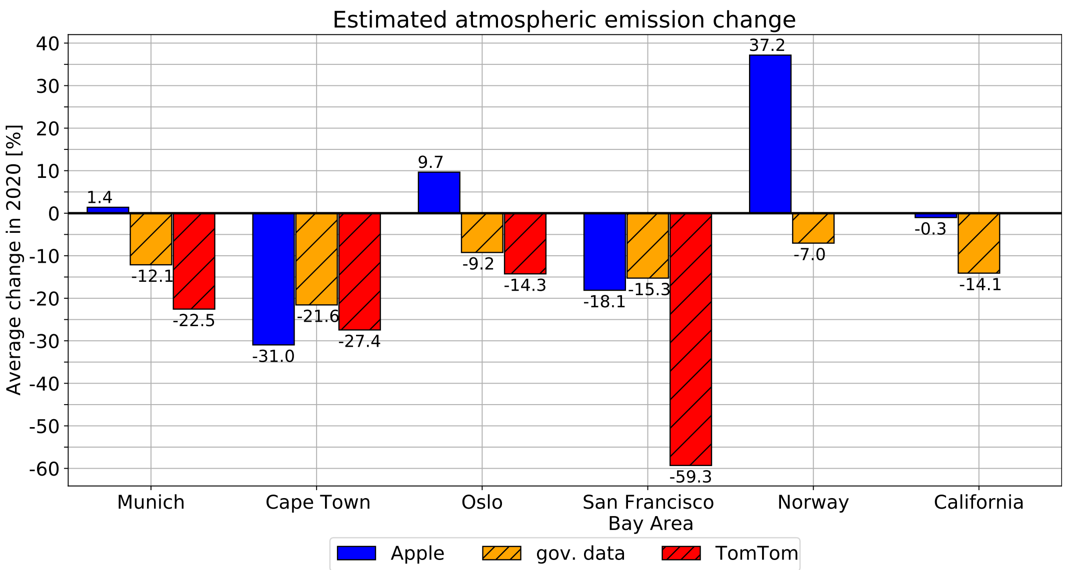

Figure 4. Estimated atmospheric emission change. Traffic emission change in the time span 01/13/2020 until 11/30/20 for six urban and rural regions. Apple data is referenced to January 13, 2020 whereas TomTom and governmental data are to 2019.

Figure 4 shows the estimated atmospheric emission change based on those datasets from January 13, 2020 until November 30, 2020. The bars show the average daily change of the time series.

We quantify the impact of the COVID-19 pandemic on governmental traffic data which ranges from a decrease of 7.0% to 21.6% depending on the region. The TomTom congestion index typically indicates a higher decrease than the governmental data. In the extreme case of the San Francisco Bay Area the TomTom data reduction is about four times higher than the governmental data reduction. Apple even shows an increase in Munich, Oslo, and Norway. In Cape Town and the San Francisco Bay Area it shows a decrease and in California it indicates nearly no change in average over the investigated period. Supplemental Figure S7 shows the same comparison but also governmental and TomTom data are related to January 13, 2020 there. Supplemental Figure S8 shows the time dependent estimated traffic emission change in 2020.

Figure 5 shows the difference in trace gas emissions since January 13, 2020 until the corresponding day on the horizontal axes when TomToms congestion index or Apples mobility data is used as a proxy for traffic changes instead of governmental traffic data following Equation 1. If the deviation is negative the usage of the mobility dataset results in a lower estimated emission number than using the local governmental data:

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

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. In Figure 5, the data are denoted as $d^{13,Jan}$, d^{2019}, and g^{2019}, depending on the baselines that are used for the referencing. In Supplemental Section S8 we use Eq. 1 with combinations of different baselines for both the local government and mobility data.

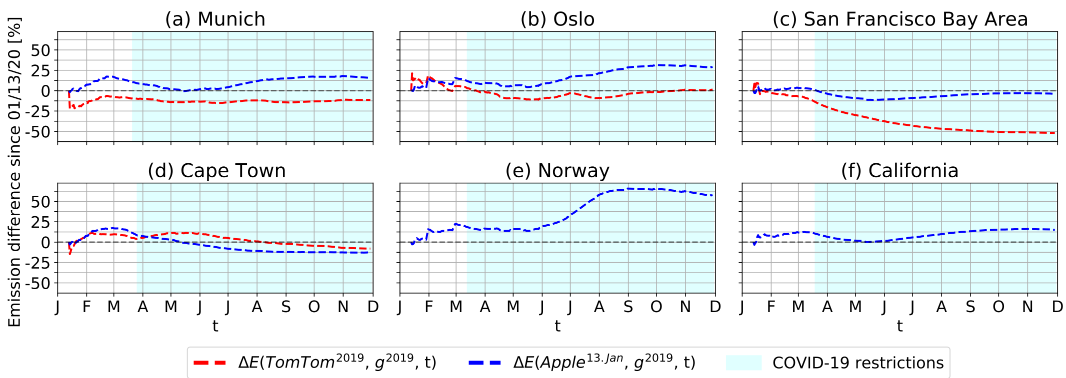

Figure 5. Timeseries of the emission difference (ΔE, Equation 1) of TomToms and Apples data compared to governmental data. The value assigned to one day is the difference in integrated emissions calculation from January 13, 2020 to the corresponding day t using Apples or TomToms data (d) instead of governmental traffic data (g) following Equation 1.

We observe in Figure 4 and 5 that the difference between emissions estimates based on governmental traffic data to estimates based on TomTom congestion index or Apple mobility data differ for 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). Reasons for this can be caused by the regional annual traffic seasonality that is not taken into account by Apple or TomTom. Relationships between TomTom and Apple data to govermental data can be linear or non-linear depending on the region (Figure 3, Supplemental Figs S6, and S7). The usual regional congestion level may also impact the TomTom congestion reduction (Supplemental Figure S4). The lack of historical data from TomTom and Apple makes it difficult to investigate the regional differences in the data. The resulting emission differences using mobility datasets are in the range of -13% to 66% and -52% to 21% for Apple and TomTom, respectively.

Taking the San Fracisco Bay Area as an example, we calculated the discrepancies in emission estimates using different datasets. We use Caltrans, California Department of Transportation (2020) VMT measure (governmental dataset) for the 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 30/11/20 the total differences in the Bay Area when using Apple instead of VMT are 0.45 Mt CO_2, 452 t NO_x, and 67 t PM which is a relative vehicle emission difference of -4.55%. Using TomTom instead of VMT results in an emission difference of 5.7 Mt CO_2, 5653 t NO_x, and 848 t PM (-56.78% in vehicle emission). The percentage error can also be observed in Figure 5 and in Supplemental Figure S9 and compared to other regions. These errors in traffic emission estimates affect the total CO_2 emissions of the San Francico Bay Area by an underestimate of -1.6% and -20% using Apple and TomTom, respectively (Supplemental Section S9).

5 Discussion and conclusions

In this study, we investigated the estimated traffic emission change in 2020 due to the COVID-19 pandemic in seven urban and rural regions using different measures of traffic and mobility. Using governmental traffic data, we identify emission reductions in the range of 7-22% compared to 2019. We compare these results to mobility data provided by Apple and TomTom and identify two major error sources in emission estimates when using them as a proxy for vehicle traffic:

1. **Referencing error.** The impact of the weekly and annual traffic cycle is significant. Use of a fixed (arbitrary) time-point reference value may yield incorrect conclusions (see Figs 1, and 2).
2. **Representation error.** The datasets investigated here measure different quantities. Local governments typically measure traffic volume and/or vehicle miles traveled, Apples mobility dataset is a measure of their request volume from navigation systems (Apple Maps), and TomToms congestion index measures urban congestion levels. Even when using the same baseline the deviation of the datasets is, again, non-trivial (Figure 3, Supplemental Figs S1, S5, S7, and S9).

These error sources do not allow us to develop a generalizable relationship between mobility data and traffic flow over all regions (see Figs 1, 3, 5 and Supplemental Figs S5, S6, S7, S8), like assumed in Liu et al. (2020) and Forster et al. (2020). Supplemental Figure S15 shows the error induced by the regression function between TomTom congestion and governmental data used in Liu et al. (2020).

We quantify vehicle trace gas emission deviations of -13% to +66% and -52% to +21% for Apple and TomTom, respectively, 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 Tom-

Tom results in transportation emission estimates that are, respectively, 0.45 Mt CO_2 and 5.7 Mt CO_2 lower than government traffic data implies, resulting in total emission estimates that differ by -1.6% and -20%.

Despite the widespread use of these mobility metrics, there is a lack of understanding about what exactly they are telling us about changes 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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