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Special Section:
The COVID-19 pandemic: linking health, society and environment

Key Points:

- Recent work used novel mobility data for assessing the impact of the COVID-19 pandemic on traffic CO_2 emissions. However, we observe errors in excess of 60%
- The relationship between mobility and traffic activity data could not be explained by a general relationship over all investigated regions

Supporting Information:

Supporting Information may be found in the online version of this article.

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What Are the Different Measures of Mobility Telling Us About Surface Transportation CO_2 Emissions During the COVID-19 Pandemic?

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Abstract The COVID-19 pandemic led to widespread reductions in mobility and induced observable changes in atmospheric emissions. Recent work has employed novel mobility data sets as a proxy for trace gas emissions from traffic by scaling CO_2 emissions linearly with those near-real-time mobility data. Yet, there has been little work evaluating these emission numbers. Here, we systematically compare these mobility data sets to traffic data from local governments in seven diverse urban and national/state regions to characterize the magnitude of errors that result from using the mobility data. We observe differences in excess of 60% between these mobility data sets and local traffic data. We could not find a general functional relationship between the mobility data and traffic flow over all the regions and observe higher deviations from using such general relationships than the original data. Finally, we give an overview of the potential errors that come from estimating CO_2 emissions using (mobility or traffic) activity data. Future work should be cautious while using these mobility metrics for emission estimates.

Plain Language Summary The government-imposed mobility restrictions due to the COVID-19 pandemic led to observable changes in our atmosphere. We identify traffic activity reductions in the range of 7%–22% in 2020 compared to that 2019 in seven diverse urban and national/state regions using traffic data from local governments. Previous studies investigating these observed changes used new data sets from tech companies that track user mobility as a proxy for traffic activity. However, our work identifies important shortcomings using these new mobility data sets to directly estimate emissions from traffic, with calculated estimated traffic activity errors larger than 60% (deviations between novel mobility data and governmental traffic flow data). Further, we could not find a simple functional relationship between these new mobility data sets and data from local governments on traffic flow, indicating that one should be cautious while using these mobility metrics to assess emissions.

1. Introduction

The COVID-19 pandemic induced widespread changes in society, affected the global economy, and has indirectly affected 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., Balamurugan et al., 2021; Dietrich et al., 2021; Tanzer-Gruener et al., 2020; Turner 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., Grange et al., 2020; Venter et al., 2020). These studies have high impact as they are cited in research, media, and also in the United Nations Emission Gap Report (UNEP, UNEP DTU Partnership, 2015). Many of these studies employed global mobility data sets from Apple Inc. (2020), Google LLC (2020), and TomTom International BV (2020) and concluded that the decrease in mobility was one of the leading reasons of decreased global GHG emissions and air pollution during COVID-19 lockdown

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periods. For example, Le Quéré et al. (2020) use data from Apple and TomTom as a proxy for vehicle activity for most of the world, and applies a linear scaling of emissions with these activity data sets. Further, Liu et al. (2020) scale EDGAR transportation emissions (Janssens-Maenhout et al. (2019), 1A3b for 2010) linearly with vehicle activity data that has been calculated by deriving a general equation of TomTom mobility data (congestion index) to vehicle counts. This functional relationship was derived from one region (Paris) and applied to all the other cities worldwide.

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 data sets can tell us about traffic activity and trace gas emissions is warranted.

Here, we investigate these measures of mobility and compare them to the data from local governments regarding their utility as a proxy for traffic activity data and CO_2 emissions from vehicle traffic. Through a series of case studies in seven urban and national/state regions, we highlight cases where the mobility data is consistent with the local governmental data on traffic flow and, importantly, cases where the mobility data is inconsistent. We then quantify the potential errors in emission estimates (e.g., Equation 2) while using these mobility data sets, with a particular focus on CO_2. We follow this with a case study examining emission estimates from Norway with mobility data and fuel sale data. We conclude with a discussion that summarizes the dominant sources for the error and the magnitude of errors that can be induced using mobility data in this manner.

2. Regions for Case Studies and Investigated Datasets

We selected seven regions (Oslo, Munich, San Francisco Bay Area, Los Angeles, Cape Town, Norway, California; 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 the availability of data from local governments on traffic. The distribution of the regions over the latitudes and the coverage of the northern and southern hemispheres enable a comprehensive data analysis. Diverse seasonal climate behaviors are covered, for example, the strong and weak temperature seasonality in Oslo and in California (Figure S2). While Norway and California are comparable in size, the population of California is around 8 times higher than that in Norway. From Table S1, we can see that all of these regions first enacted restrictions on the mobility of their populations between March 13 and March 26 in 2020. We have included the analysis of Los Angeles in Section S9.

It is important to note that the measures of mobility do not all report the same quantity. Additionally, the metric reported in the mobility data sets 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 the 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 min and the congestion index currently is 50%, then the trip takes 15 min 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.

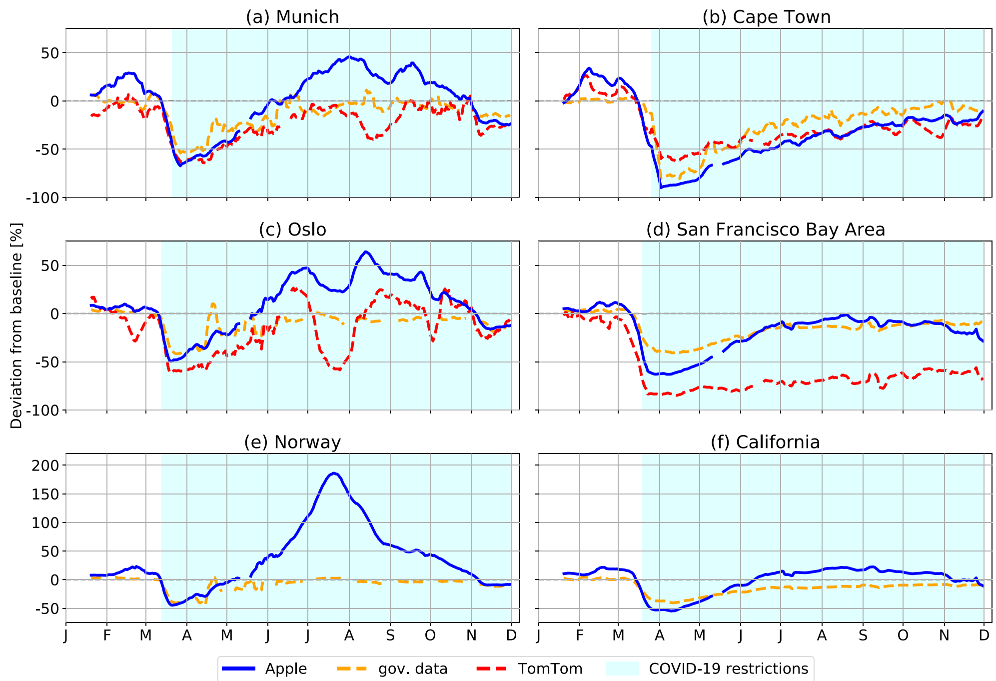

Figure 1. Time series trend comparison of different mobility and traffic data sets. Apple data are relative to its request volume on January 13, 2020. There is no 2019 data for the Apple mobility index as this product was only made public in response to the COVID-19 pandemic. The governmental traffic data each weekday is related to the same weekday of the same calendar week in 2019 and for the TomTom data each weekday is related to the annual average congestion of that weekday in 2019. A 7-day rolling mean is applied to the data to remove the weekly cycle.

The data set from Google (Google LLC, 2020) has also been used in recent studies (e.g., Forster et al., 2020; Venter et al., 2020), however, this data set provides information about the stay of people at different locations such as transit stations. As such, it does not directly inform us about the transportation sector. We have included an analysis of this data set in Section S1 due to its use in recent work.

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 (Bayerisches Landesamt fuer Umwelt (LfU), 2020; Caltrans, California Department of Transportation, 2020; Western Cape Government, Road Network Information System, 2020; Statens vegvesen, 2020). We have, further, collected monthly fuel sale data for Norway (Statistics Norway, 2021).

From Figure 1, we can see that all data sets 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 (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 the 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 these novel mobility datasets.

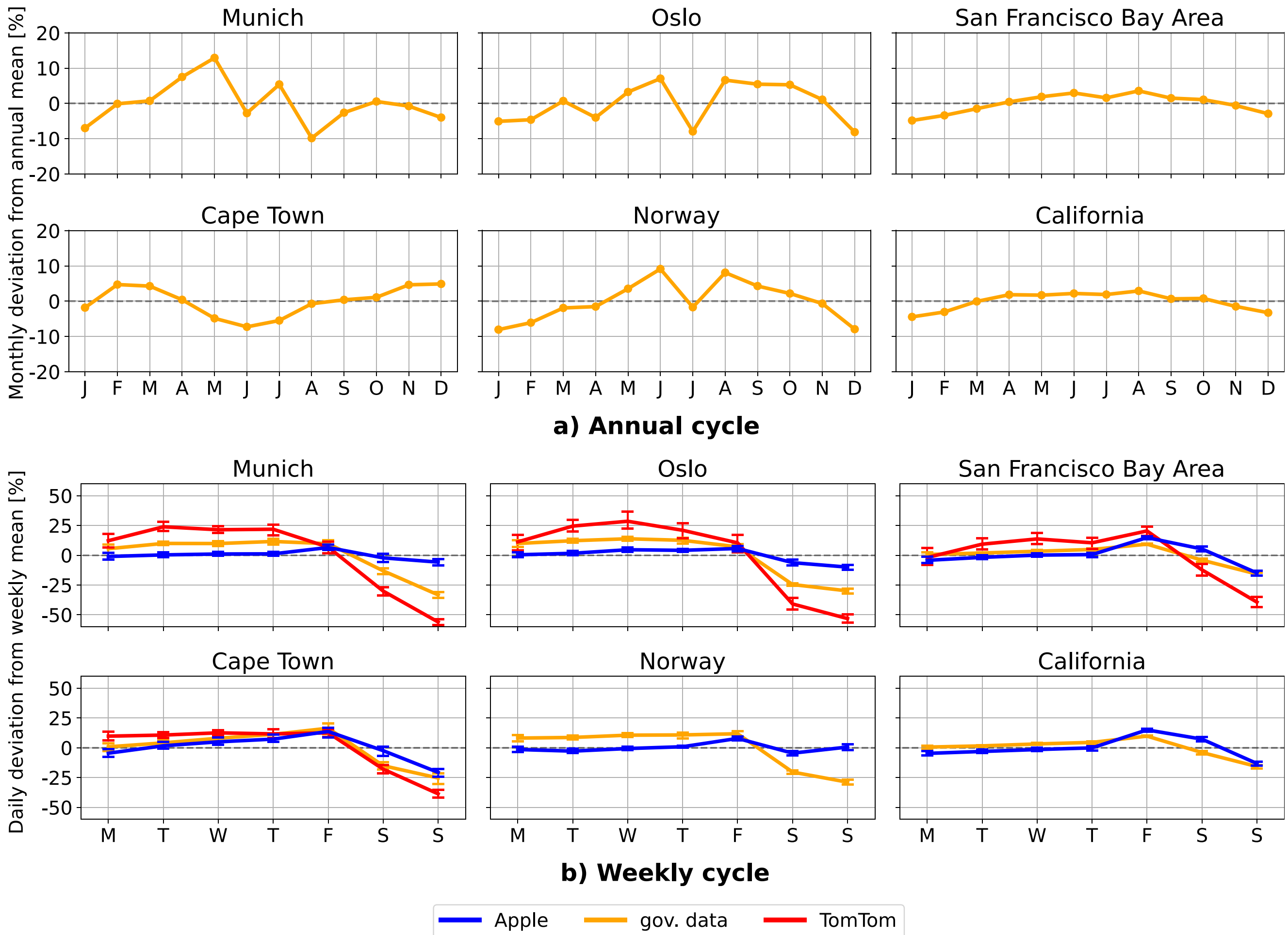

Figure 2. Annual and weekly cycle of traffic and mobility data (a) Annual traffic cycle. Deviation of the mean monthly local governmental data of the corresponding month in 2019 to the mean of the year 2019. (b) Weekly traffic cycle. Deviation of the daily data of the corresponding weekday to the mean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

3. Assessing Differences Between the Activity 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 underlying 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 deviation peaks 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 the investigated regions. The traffic seasonality at higher latitudes is larger than that at lower latitudes, for example, in California.

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 the regions show a pronounced decrease in the 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 the TomTom and the local government data, but not the Apple mobility data. A similar pattern is seen in Oslo and Cape Town, but is notably different from that of San Francisco where all data sets indicate the largest, positive, anomaly on Friday. Apple data indicates the largest positive anomaly on Fridays across all the regions. The lower traffic values seen on weekends in the local governmental data and TomToms congestion index is also notably smaller in the Apple Maps mobility data.

The annual traffic cycle (Figure 2a) and the weekly traffic cycle (Figure 2b) reveals the importance of taking annual and weekly seasonality into account, which is, however, not the case for the Apple data. TomTom data includes weekly cycles, but neglects its annual cycle. Figure S1 shows the time series of all data sets related to January 13, 2020. We observe large differences between data sets which reveal 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 the differences between the 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 data sets to their value on January 13, 2020. The coloring of the dots represents the distance to the first day of the 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 that the relationship between mobility data and actual traffic counts is both non-linear and unique to each region. This non-linearity and location-specific relationship would likely induce errors in a global estimate based on a single city (e.g., Liu et al., 2020). Removing the impact of weekly cycles by only comparing weekly means shows a similar trend (Figure S5). This indicates that future work should be cautious while 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 Figure S13, 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 the original governmental traffic data.

4. Quantification of the Difference Between Mobility and Traffic Activity Data

In the previous section, we show that there are differences on a daily, weekly, and monthly timescales between the activity data derived from mobility datasets and governmental traffic data. Figure 4 shows the estimated traffic activity change based on each of those data sets. Applying a linear scaling of emissions with the activity data following Equation 2, as also assumed in Le Quéré et al. (2020) and Liu et al. (2020), these changes would directly translate to estimates for surface transportation CO_2 emission changes. Figures 4a and 4b cover the time from January 13, 2020 until November 30, 2020 and from March 01, 2020 until May 31, 2020, respectively. The bars show the average daily change of the time series with the standard deviation as error bars. Additionally, to the original datasets, we have applied the sigmoid function from the Carbon Monitor (Liu et al., 2020) that intends to map the TomTom data to traffic fluxes. The equation was derived by comparing the TomTom data to the governmental data in Paris and applied to other cities in the world. Further, we have compared the Carbon Monitor's estimates of traffic flux to the governmental data in our urban study regions on a daily basis in Figure S13.

We quantify the impact of the COVID-19 pandemic on the governmental traffic data, which ranges from a decrease of 7%–22% for January to November, depending on the region. From Figure 4a, we can see that the TomTom congestion index typically indicates a stronger decrease in traffic than that in the governmental data. In the extreme case of the San Francisco Bay Area, reduction in the TomTom data is about four times higher than the reduction in the governmental traffic data. 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. The mapping function of the Carbon Monitor (Liu et al., 2020) shows a notably smaller reduction in the activity in three of the four urban regions.

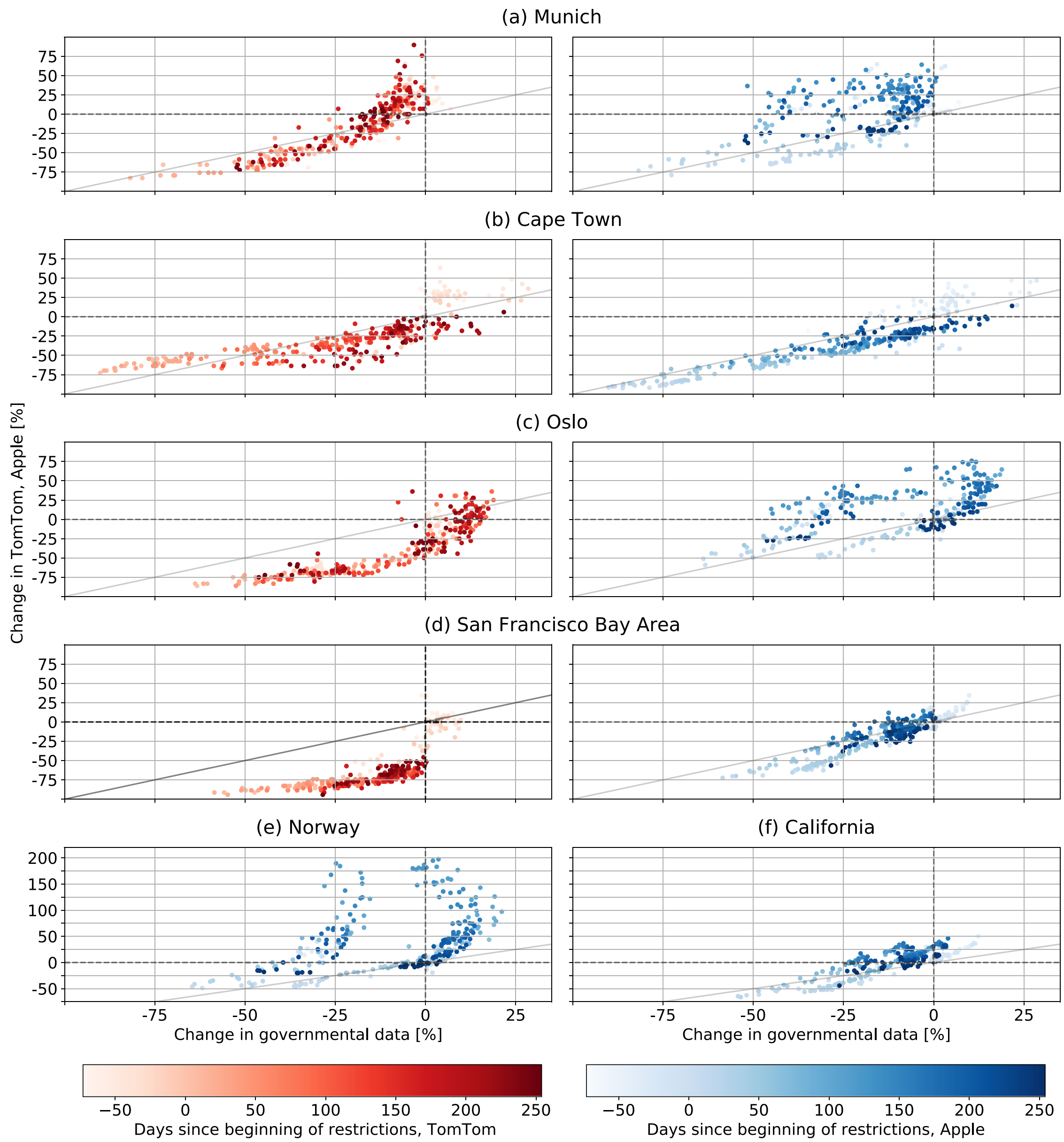

Figure 3. Comparison of different measures of traffic flow. The scatter shows the daily comparison between the governmental data to the Apples mobility data and TomToms congestion index. All data sets are referred to their value on January 13, 2020. The coloring of the dots is done by the distance to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

Figure 4b shows a different pattern than that in sub-figure a. Here, we only investigate the time from March to May (lockdown period). Apple agrees with the governmental data in Oslo and is close in Munich. Notably, the mapping function of Liu et al. (2020) disagrees strongly in Munich and Cape Town. Interestingly, the output of the mapping function deviates in Munich and Cape Town, even stronger from the governmental traffic activity data than the original TomTom data. Figure S7 shows the same comparison, but with the governmental and TomTom data related to January 13, 2020 there.

Figure 5 shows the difference in activity data since January 13, 2020 until the corresponding day on the horizontal axes when the TomTom's congestion index or the Apple's 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 data set results in a lower estimated activity than while using the local governmental data:

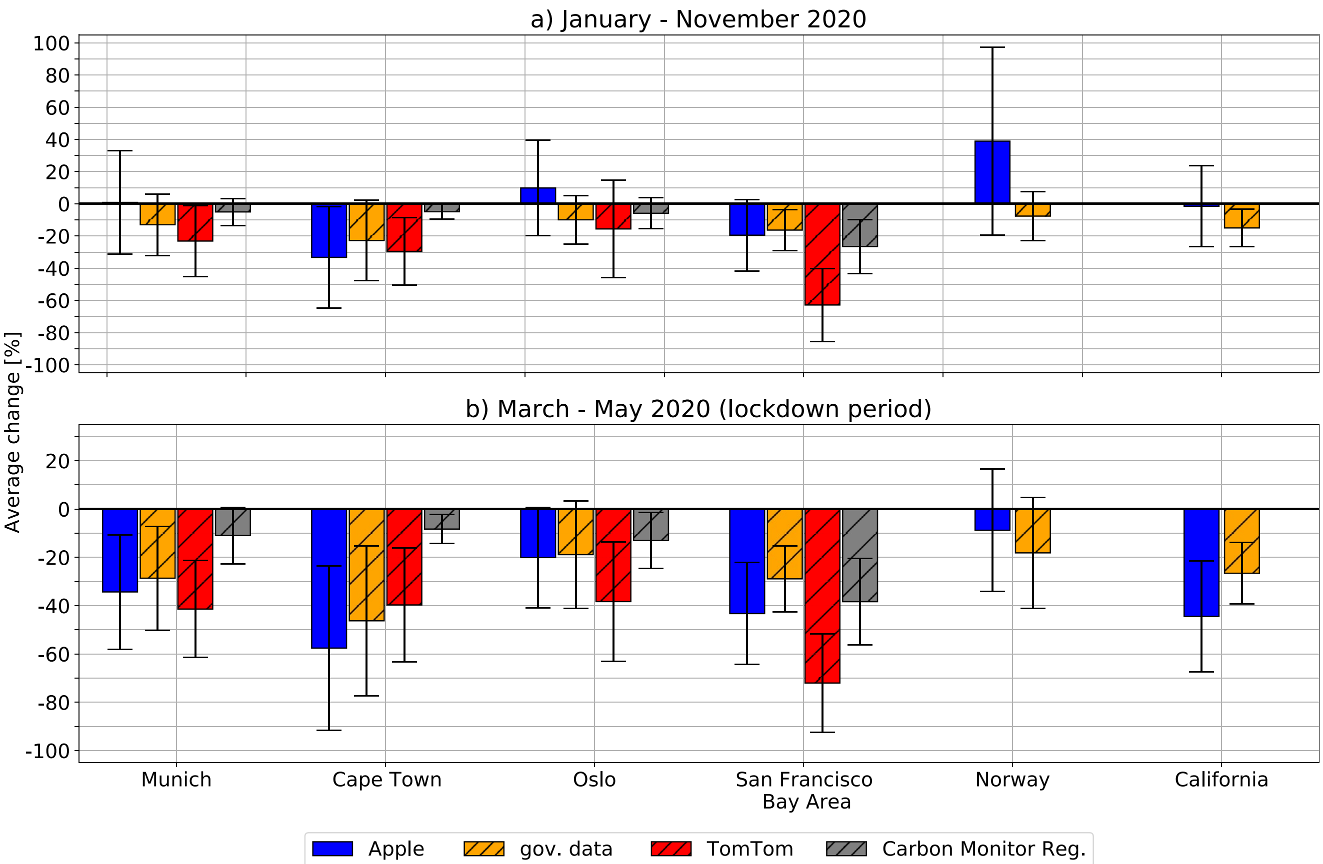

Figure 4. Traffic and mobility activity change in the time span 01/13/2020 until 11/30/20 (a) and 03/01/2020 until 05/31/20 (b) for six urban and national/state regions. The Apple data are referenced to January 13, 2020 whereas the TomTom, governmental, and Carbon Monitor (Liu et al., 2020) data are to 2019. The bars represent the activity change averaged over all the days of the respective time span. The error bars represent the standard deviation of the daily activity change over that time span. By applying a linear scaling with transportation emissions as in Equation 2, the bars would translate to estimated traffic emission reductions.

$$D(\Delta A_m, \Delta A_g, t) = \frac{\sum_{i=1}^{t} \left(\Delta A_{m,i} - \Delta A_{g,i} \right)}{\sum_{i=1}^{t} \Delta A_{g,i}} \tag{1}$$

where D is the difference in traffic activity estimates on the vertical axes in percent; t is the day on the horizontal date axes; ΔA_g the local governmental data; and ΔA_m are the datasets of Apple or TomTom. In Figure 5, the data are denoted as follows: $\Delta A_m^{13.\,Jan}$, ΔA_m^{2019}, and ΔA_g^{2019}, depending on the baselines that are used for referencing. In Section S8, we use Equation 1 with combinations of different baselines for both the local governmental and mobility data.

We observe in Figures 4 and 5 that the difference between activity estimates based on the governmental traffic data to estimates based on the TomTom congestion index or Apple mobility data differ for each study region, and depend on the time point of investigation (day t after the reference day). The data sets may 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 the TomTom and Apple data to the governmental data can be linear or non-linear depending on the region (Figure 3, Figures S6 and S7). The usual regional congestion level may also impact the TomTom congestion reduction (Figure S4). The lack of historical data from TomTom and Apple makes it difficult to investigate the regional

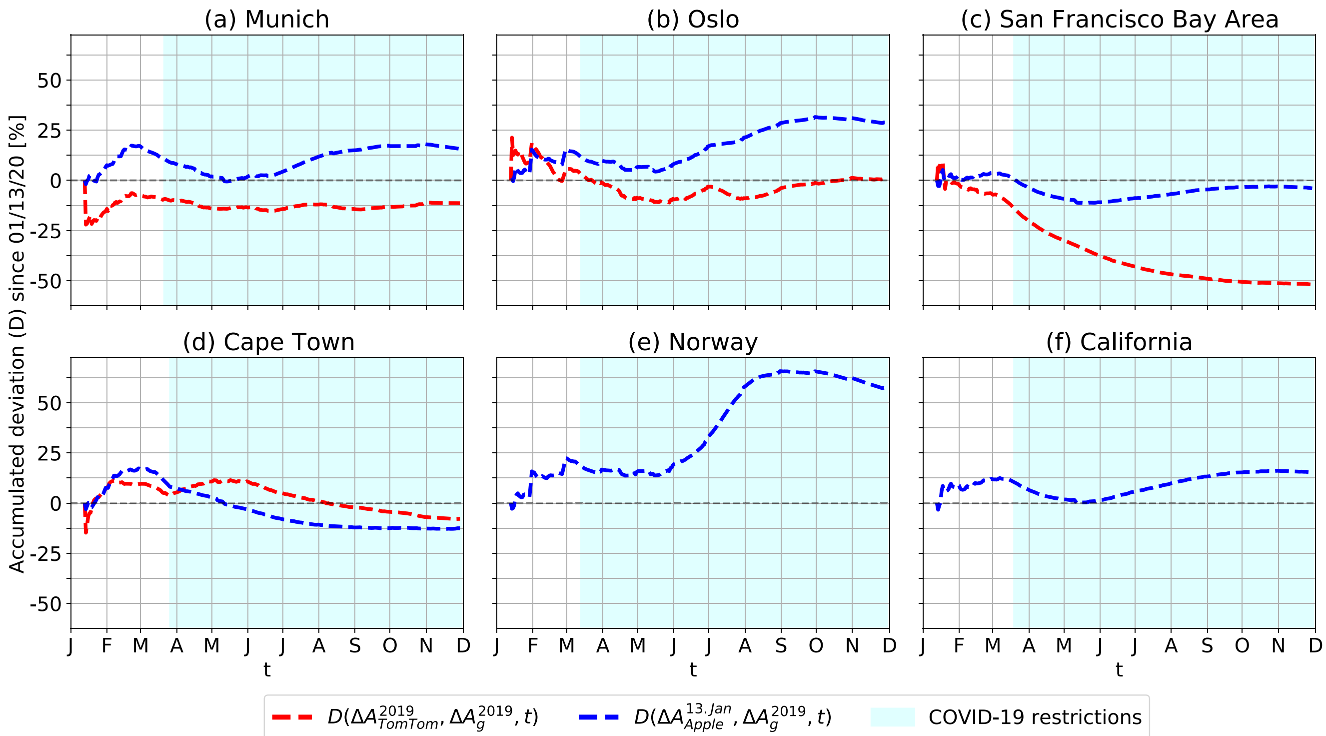

Figure 5. Time series of the accumulated deviation (D, Equation 1) of the TomTom and Apple data compared to the governmental data. The value assigned to one day is the difference in the integrated activity calculation from January 13, 2020 to the corresponding day t using Apple's or TomTom's data (ΔA_m) instead of the governmental traffic data (ΔA_g) following Equation 1.

differences in the data. The resulting estimated traffic activity differences using mobility data sets are in the range of −13%–66% and −52%–21% for Apple and TomTom, respectively.

5. Impact of Mobility Datasets on Estimated Atmospheric Emission Change

We identify that the 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?"

Le Quéré et al. (2020) use data from Apple and TomTom as a proxy for vehicle activity for most of the world using the following relationship:

$$\Delta CO_2 = CO_2 \cdot \delta S \cdot \Delta A \tag{2}$$

where ΔCO_2 is the calculated emission change, CO_2 are the mean daily emissions from (among others) Friedlingstein et al. (2019) for 2017 to 2019, δS is the fraction of emissions in each sector, and ΔA is the change of activity data for each sector. Emissions are, therefore, scaled directly with, among others, mobility data sets from Apple and TomTom for the surface transportation sector. Also, Liu et al. (2020) scale emissions linearly with activity data. We can see from Figures 3–5 that mobility data and traffic counts are fundamentally different measures. Applying the functional relationship from the Carbon Monitor that was derived between the TomTom and traffic count data in Paris, induce larger errors than the original TomTom data occur (see Figure 4). From Figure 3, we further observe that there is no generalizable relationship between TomTom or Apple and governmental traffic count data.

In Figure 4, we show differences in ΔA in Equation 2 between the studied measures of traffic activity. Scaling emissions using the mobility or traffic data (Equation 2) like Le Quéré et al. (2020) or Liu et al. (2020), the resulting relative CO_2 emission change equals the activity data change in Figure 4. As discussed before, we see major deviations of the mobility data set to the governmental traffic data. These differences depend

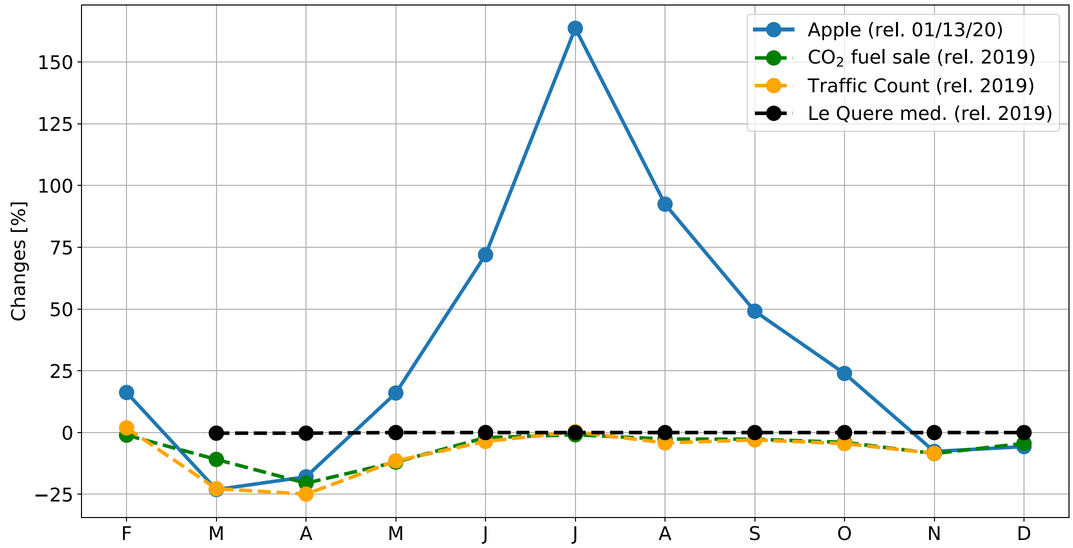

Figure 6. Fuel based CO_2 emission estimate versus activity data estimates for Norway. Calculated CO_2 emissions for Norway following fuel sale data from Statistics Norway (2021) and emission factors from Statistics Norway (2016) (motor gasoline: 3.13 $tons_{CO2}/ton_{gasoline}$, diesel: 3.0 $tons_{CO2}/ton_{diesel}$), Le Quéré et al. (2020) estimate, Apple Inc. (2020), and governmental traffic count data (Statens vegvesen, 2020) in monthly resolution. Apple data are pegged to January 13, 2020 whereas the other data sets are relative to the corresponding month in 2019.

on the region and time-point of investigation (see Figures 1, 3 and 5). The chosen activity data has, therefore, a major impact on the estimated emission reductions during the COVID-19 lockdowns and beyond.

Figure 6 shows emission changes assessed while using the Apple mobility index for driving, fuel sale data, governmental traffic count data, and the Le Quéré et al. (2020) medium estimate for Norway in monthly resolution. We do not show the TomTom data as it is limited to urban areas. Further, the Carbon Monitor (Liu et al., 2020) does not provide explicit data for Norway. The fuel based emissions are calculated by multiplying the fuel sales of Norway (Statistics Norway, 2021) with Norwegian emission factors for diesel and gasoline (Andres et al., 2011; Prentice et al., 2001; Statistics Norway, 2021, 2016). We observe that the emission estimates based on the governmental traffic data are generally in agreement with fuel based CO_2 estimates, with March as the only exception. The estimate using Apple deviates significantly from the fuel sale estimates in the summer months. The Le Quéré et al. (2020) estimate is close to zero for the full year 2020. This also accounts for the low and high Le Quéré et al. (2020) estimate. Here, we focus on CO_2 from the transportation sector. The relative importance of trucks and cars will differ for species like NO_x and may, therefore, yield different patterns. We limit the analysis of fuel based CO_2 estimates to Norway due to a lack of fuel sale data in our other study regions or at urban scale.

The linear scaling of emissions with the (estimated) traffic activity data or proxies for traffic activity neglects the important parts of emission calculation. The activity data does not distinguish between vehicle types. The government-imposed restrictions due to COVID-19 primarily affected the transportation sector and social activities. Freight vehicles and diesel trucks largely continued operation. In Oslo, private cars only account for 39% of the total GHG emissions in the surface transportation sector (Guillaume Simonet, 2019). There can also be a non-linear response in emissions to traffic flow. For example, the fuel efficiency of vehicles as a function of speed is non-linear (Caltrans, California Department of Transportation, 2020), and a small change in total traffic can lead to a large change in congestion. We observe in the San Francisco Bay Area that a decrease in the metric vehicle miles traveled is correlated to an increase in average speed (Figure S15). The approach of scaling traffic emissions linearly with the traffic activity data is a recent method and not proven against fuel based approaches like the one suggested by Prentice et al. (2001). It is unknown how exactly the neglecting shares of vehicle types and emission factors impact the emission estimated for the regions presented here. Oda et al. (2021) shows the difference of emission estimates based on fuel sale, Apple data, Google data, Le Quéré et al. (2020), and Liu et al. (2020) in Japan and presents that fuel based CO_2 emission reductions are approximately double as traffic count–based estimates for April and May 2020 (lockdown period in Japan). Further, it is shown that the deviations to the mobility indices and estimates from Le Quéré et al. (2020) and Liu et al. (2020) to fuel based estimates are in the range of −82%–38% in April and May lockdown period. Models like the California Air Resources Board's EMFAC (2014) could be used to calculate emissions based on vehicle counts. These bottom-up models show a good alignment with fuel based inventories (McDonald et al., 2012). Further analysis and investigation of the novel data sets might induce a new generation of bottom-up emission estimate approaches or models.

6. Conclusions

In this study, we investigated and evaluated the usability of novel mobility data sets from tech companies as proxies for traffic activity and CO_2 emissions in seven urban and national/state regions. Using the governmental traffic data, we identify traffic activity reductions in the range of 7%–22% compared to that in 2019. We compare these results to the mobility data provided by Apple and TomTom, and quantify the vehicle deviations of −13% to +66% and −52% to +21% for Apple and TomTom, respectively, compared to the traffic count data from the local government. These percentage values depend on the region of interest and time of investigation. We identify that the deviations are driven by referencing (using a fixed referencing point may yield incorrect conclusions, see Figures 1 and 2) and representation errors (the data sets measure different events, Figure 3, Figures S1, S5, S7, and S8).

These error sources do not allow us to develop a generalizable relationship between the mobility data and traffic flow over all the study regions (see Figures 1, 3 and 5 and Figures S5, S6, S7, and S8), as assumed in Liu et al. (2020) and Forster et al. (2020). Figure 4 and Figure S13 show the error induced by the Carbon Monitor (Liu et al., 2020) using a nonlinear function between the TomTom congestion and governmental data. In some instances, we observe the nonlinear approximation to perform worse than the original TomTom congestion data when compared to the traffic activity data it aims to estimate.

Le Quéré et al. (2020) scaled emissions linearly with the mobility data. It is unknown how exactly these estimates compare to fuel-based inventories in all the study regions. The approach neglects, for example, changing emission factors due to an increase in speed (Figure S15) or, importantly, the share of vehicle types. The restrictions on society were primarily on transportation and social activities, while freight operations continued. We observe big deviations of Apple to a fuel based CO_2 emission estimate in Norway. Emission estimates based on governmental traffic activity data agrees with the fuel based approach, except for the COVID-19 governmental lockdown period.

We therefore, identify two major error sources in traffic emission estimates based on the mobility data from Apple or TomTom: (a) Using mobility data as a proxy for traffic activity. (b) Scaling surface transportation emissions with non-fuel based activity data.

Despite the widespread use of these mobility metrics, there is a lack of understanding about what exactly they are telling us about changes in CO_2 emissions. Here, we quantified the potential errors that might be inferred by using these mobility metrics as a proxy for the governmental traffic activity data and discuss about further errors that come with linear scaling of emissions with the traffic activity data. The findings presented here should serve to caution others from directly using these mobility measures as a proxy without additional investigation or adaptation. Further analysis is necessary to quantify the exact error that result from using the mobility data sets in combination with the novel approach of scaling emissions with non-fuel based activity data in comparison to the usual approaches for example, from Oda et al. (2018); Janssens-Maenhout et al. (2019). Here, a one-by-one comparison might give us more insights and help us to understand how to use the mobility data more accurately to quantify emissions, especially in near-real-time and daily resolution.

Conflict of Interest

The authors declare no conflicts of interest relevant to this study.

Data Availability Statement

TomTom data: https://www.tomtom.com/traffic-index/, Apple data: https://covid19.apple.com/mobility, Governmental data: Norway: https://www.vegvesen.no/, California: http://pems.dot.ca.gov/, Munich: https://www.lfu.bayern.de/, Cape Town: https://rnis.westerncape.gov.za/. All collected mobility and traffic data is also included in the supplement. The governmental data is normalized by its maximum value.

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