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Social-distancing fatigue: Evidence from real-time crowd-sourced traffic data

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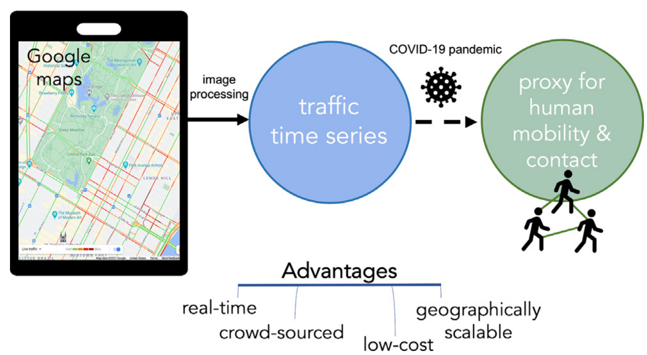
HIGHLIGHTS

- Real time traffic maps can be data-mined for human mobility.
- The COVID-19 pandemic dramatically impacted traffic in NYC.
- Social-distancing fatigue occurred ~2 months before stay-at-home orders were lifted.
- Both rush hour and average traffic were dampened due to COVID-19.

GRAPHICAL ABSTRACT



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ABSTRACT

Introduction: To mitigate the COVID-19 pandemic and prevent overwhelming the healthcare system, social-distancing policies such as school closure, stay-at-home orders, and indoor dining closure have been utilized worldwide. These policies function by reducing the rate of close contact within populations and result in decreased human mobility. Adherence to social distancing can substantially reduce disease spread. Thus, quantifying human mobility and social-distancing compliance, especially at high temporal resolution, can provide great insight into the impact of social distancing policies.

Methods: We used the movement of individuals around New York City (NYC), measured via traffic levels, as a proxy for human mobility and the impact of social-distancing policies (i.e., work from home policies, school closure, indoor dining closure etc.). By data mining Google traffic in real-time, and applying image processing, we derived high resolution time series of traffic in NYC. We used time series decomposition and generalized additive models to quantify changes in rush hour/non-rush hour, and weekday/weekend traffic, pre-pandemic and following the roll-out of multiple social distancing interventions.

Results: Mobility decreased sharply on March 14, 2020 following declaration of the pandemic. However, levels began rebounding by approximately April 13, almost 2 months before stay-at-home orders were lifted, indicating premature increase in mobility, which we term social-distancing fatigue. We also observed large impacts on diurnal traffic congestion, such that the pre-pandemic bi-modal weekday congestion representing morning and evening rush hour was dramatically altered. By September, traffic congestion rebounded to approximately 75% of pre-pandemic levels.

Conclusion: Using crowd-sourced traffic congestion data, we described changes in mobility in Manhattan, NYC, during the COVID-19 pandemic. These data can be used to inform human mobility changes during the current pandemic, in planning for responses to future pandemics, and in understanding the potential impact of large-scale traffic interventions such as congestion pricing policies.

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1. Introduction

The COVID-19 pandemic threatens almost every single country on Earth (Li et al., 2020; World Health Organization, 2020). To curb the pandemic and prevent overwhelming the healthcare system with COVID-19 cases, social-distancing policies such as school closures, non-essential business closures, curfews, and stay-at-home orders have been put into place. Social-distancing policies, specifically quarantines, are some of the oldest and most utilized strategies for epidemic control (Tognotti, 2013). Social distancing policies function by reducing physical contact and decreasing human mobility; adherence can substantially reduce transmission (Jarvis et al., 2020) and case counts (Alagoz et al., 2020). Thus, quantifying human mobility and social-distancing compliance, especially at high temporal and spatial resolution, is critical for controlling the epidemic.

Several measures of social-distancing compliance have been used previously in the literature. Studies evaluating individual-level adherence to social-distancing policies frequently use self-report through online surveys (Moore et al., 2020; Zhao et al., 2020; Xie et al., 2020). While these methods are very useful for evaluating determinants of adherence, they are not as useful for real-time epidemic monitoring because they are time- and labor-intensive and only capture a snapshot of the population's behavior in a small sample at a single timepoint. In contrast, highly resolved data such as mobile phone call records or locations can be used to measure social-distancing (Charoenwong et al., 2020) and to inform mobility components of infectious disease transmission models (Tizzoni et al., 2014). These measures, especially if publicly available, can contribute to epidemic monitoring. One such option is vehicular traffic condition smartphone apps, which base their maps on cellphone movement data. Traffic congestion maps are publicly available, updated in real-time, and can be used for public health research. For example, we have previously shown that colors in Google traffic maps correspond to relative vehicle speed, and used this information to infer traffic-related air pollution (Hilpert et al., 2019).

App-based traffic information offers a pathway for assessing social-distancing, as increased traffic congestion is indicative of spending time outside the home that may result in opportunities for human interaction and contact. In fact, traffic data has been used to evaluate mobility during the pandemic in South Korea, finding that in some cities increases in traffic were correlated with increases in cases, but that in others traffic and cases were negatively correlated (Lee et al., 2020). Here we analyzed time series of traffic congestion that we derived from app-based maps. We quantify changes in traffic in the Manhattan borough of New York City (NYC) during the COVID-19 pandemic (January 1 to December 31, 2020). Our objective was to describe how social distancing interventions impacted population-level patterns of mobility throughout various stages of the pandemic.

2. Methods

From January 1 through December 31, 2020, we obtained 12 tiles from Google traffic maps to view Manhattan's entire street network every three hours in real time. Briefly, the traffic map area was defined as a rectangular array of square tiles, specifying the latitude and longitude of the centroid of the array, the number of pixels along one side of a square tile, the zoom level, and the number of tiles in the x and y direction. The zoom level can be chosen such that only traffic on major roadways and arteries is shown, or such that even traffic on small side streets can be identified (as done here, with zoom equal to 15 and a corresponding pixel size of ~4.8 m at the equator). For full details of this process, including equations and constants for calculating the appropriate zoom level and defining the geographic extent of the area to be downloaded, and scripts for displaying, downloading, automating, and merging the downloaded traffic tiles into one image, please see Hilpert et al. (2021).

We used image processing methods, as described previously in Hilpert et al. (2019) to identify the color-coded road segments. Color codes indicated four traffic categories: (i) green for free-flowing traffic, (ii) orange for medium traffic, (iii) red for traffic congestion, and (iv) maroon for severe traffic congestion. The colors are proxies for vehicle speed (relative to the road speed limit) (Weitz, 2009; Wikipedia, 2017) and have been ground-truthed with multiple vehicle speed measures, including using a traffic radar device (Hilpert et al., 2019), odometer readings from a driven vehicle (Zalakeviciute et al., 2020), and another traffic app (Waze) (Zalakeviciute et al., 2020). In the images, we first reduced the number of possible colors from 16.8 million to 256 to simplify the analysis. Since some colors used to indicate traffic congestion on road segments could also be used in the background map without the traffic layer, we identified the background map. This map was defined to consist of those pixels in the traffic map that over a 2-week period in time did not assume the green and either orange or red congestion color. Traffic color were then only analyzed in the "image background" of the background map, which one can loosely term the active street network of the traffic map. In summary (Hilpert et al., 2019), map pixels for each of the four colors were counted in the active street network and time series generated of the percent of the geographic map area (not the percent of total road pixels) covered by each color.

To investigate changes in traffic congestion during the pandemic, we first characterized all four time series, but then restricted further analysis to the time series of red traffic congestion given its clear pandemic-related signal (e.g., decrease in April) and simpler interpretability (increases in red coverage indicate increases in congestion). We did this to avoid redundancy in analysis since all color coverage time series showed correlated temporal patterns. There were substantial changes in traffic congestion over the course of the pandemic and we captured this variation by partitioning the time series into four distinct time periods, which we refer to as COVID periods. We individually fit a generalized additive model (GAM) (Wood, 2017) to each COVID period.

GAM models were constructed to describe and predict the time series of percentage of total map area covered by traffic congestion, (T_t) using two discrete predictor variables: hour of day, h_t, which can assume values 0, 3, 6, 9, 12, 15, 18 and 21; and the binary variable w_t indicating whether a traffic map describes traffic on weekdays ($w_{1,\,t}$) or during weekends ($w_{2,\,t}$). We fitted the following model to the measured T_t, $w_{1,\,t}$, $w_{2,\,t}$ and h_t data:

$$T_t = a_0 + w_{1,t}\, s_1(h_t) + w_{2,t}\, s_2(h_t) + \epsilon_t \tag{1}$$

where a_0 is the intercept (representing mean color coverage), and s_1 and s_2 are cyclic cubic regression splines with 8 degrees of freedom and zero mean. Degrees of freedom were selected using the generalized cross-validation criterion. The fitted models were then used to predict congestion levels hourly for a weekend and weekday, with 95% confidence intervals. Due to the morning and evening rush hour, traffic congestion displayed a 24-h periodicity. The range of the diurnal fluctuation was measured as the deviation from the intercept.

To investigate potential social distancing fatigue (increased mobility before relaxation of stay-at-home policies), we applied seasonal decomposition of time series by Loess (STL) (Cleveland et al., 1990) to the data from March 14 to June 16, a period including the *NY on PAUSE* policy intervention and the first stage of New York's reopening (Phase 1). This analysis decomposed the time series into a periodic component, time trend, and the remainder (or residual). Prior to running the analysis, missing observations ($n = 54$) were imputed using predictions from the GAM models.

All analyses were conducted in R version 3.5.1 (R Foundation for Statistical Computing, Vienna, Austria). Simon Wood's mgcv package was used to fit GAMs (Wood, 2011). STL analysis was completed using the `stl` function in the stats package. R code and data for this analysis can be found at doi:10.5061/dryad.7sqv9s4s8 (Shearston et al., 2020).

3. Results

We found abrupt decreases in traffic congestion in Manhattan following school closures and the implementation of stay-at-home orders (*NY on PAUSE*). For a list of policies implemented by New York State and NYC in response to the COVID-19 pandemic, please see Supplemental Table 1. A map of the study area is shown in Fig. 1, with colors representing the crowd-sourced traffic data. There was a dramatic decrease in traffic congestion after the implementation of social distancing policies. Stark differences in the proportion of green free-flowing traffic are readily apparent on the ring roads that trace the edges of Manhattan Island, as well as the main entry points, including the George Washington Bridge in the north and all tunnels and bridges in the south.

Time series of the four congestion colors (Fig. 2) reveal abrupt decreases in traffic congestion after March 14, the weekend before New York public school closure, with simultaneous increases in free-flowing traffic occurring. Importantly, we observed a steady increase in traffic congestion before *NY on PAUSE* ended on June 8th. This increase was most apparent in the red traffic congestion series, where traffic congestion appears to begin increasing on approximately May 1 and continues increasing up until about July 1. These increases occur before the end of stay-at-home orders and are indicative of social-distancing fatigue.

We identified four COVID Periods where traffic congestion changed markedly and fit each with a GAM model (Eq. (1)). The Pre-COVID Period was defined as the start of the time series (January 1) through March 13, before congestion began to decrease dramatically. COVID Period 1 was defined as March 14 through May 19. Around May 19th traffic congestion started to increase to the point that the model began poorly fitting the data; therefore, we defined COVID Period 2, which was May 20 through June 16, during which traffic congestion continued increasing. COVID Period 3 was June 17 through the end of the time series (December 31), where a more stable traffic pattern emerged.

Morning and evening rush hour impose a periodic cycle to traffic patterns, seen as daily peaks and troughs in traffic (Fig. 2). The pandemic not only caused changes in traffic trends, but also drove changes in the period cycle. In addition to the daily periodicity, there was also a weekly cycle where congestion was elevated during the five consecutive weekdays and was dampened during the two consecutive weekend days. The weekly cycle was most apparent in the Pre-COVID period and in the most recent period, COVID Period 3.

Mean percent area with red traffic congestion changed dramatically throughout 2020 (Table 1). Mean percent area with red traffic congestion (equivalent to the model intercept) was highest during the pre-COVID time period, and then decreased abruptly during COVID Period 1 (from a mean of 0.99% to 0.41%) before steadily increasing for COVID Periods 2 and 3. By COVID Period 3, the mean percent area with red traffic congestion had rebounded to about 75% of the pre-pandemic average.

The rebound in red congestion coverage began far in advance of the implementation of Phase 1 reopening (Fig. 3, second panel). In STL analysis of COVID Periods 1 and 2, congestion appears to increase from approximately April 13th onward, while Phase 1 reopening did not begin until June 8 (right dashed line).

In addition to these changes in traffic trends, the pandemic substantially altered daily traffic periodicity, such that during the height of the pandemic in NYC in the Spring, there was little differentiation between weekday and weekend traffic patterns (Fig. 4, tan lines). During the Pre-COVID period (gray lines) rush hour peaks were highest, with weekdays demonstrating a clear bimodal distribution with peaks around 9 am and

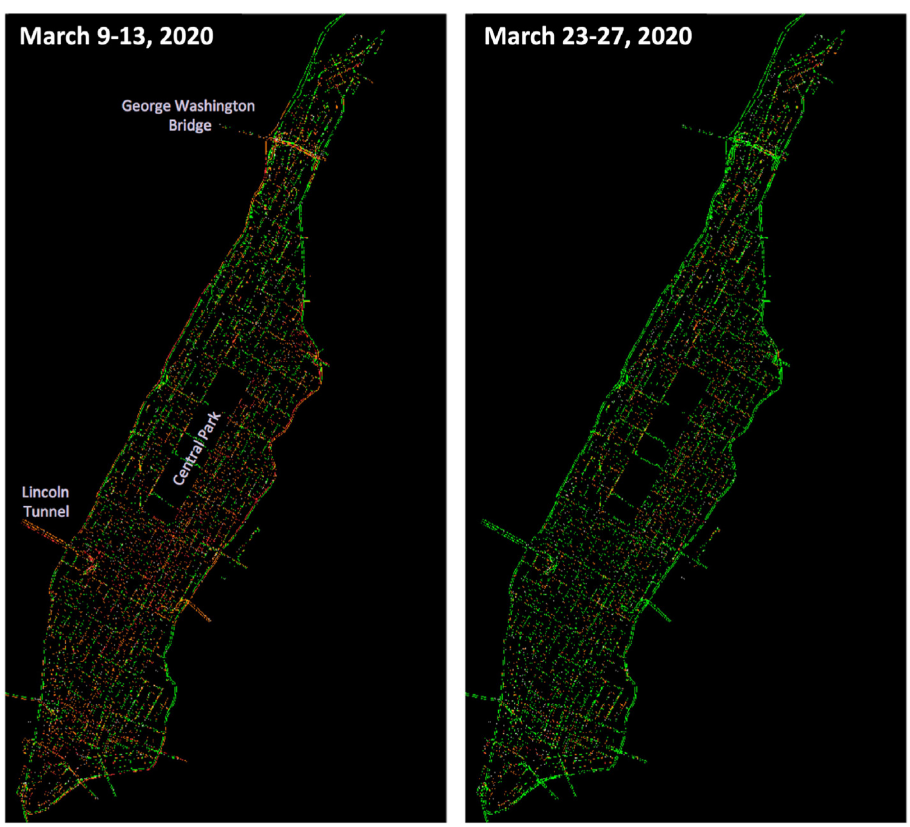

Fig. 1. Pre- and Post-Pandemic Traffic. 5-day average traffic congestion in Manhattan during the 9:30 am weekday morning rush before (March 9–13) and after (March 23–27) school closures and stay-at-home orders (*NY on PAUSE* policies) went into effect in New York City. Red and orange indicates traffic congestion, while green indicates free-flowing traffic. After the implementation of *NY on PAUSE* policies, traffic became free-flowing in the ring roads surrounding Manhattan, as well as the main entry points, including the George Washington Bridge in the north and all tunnels and bridges in the south.

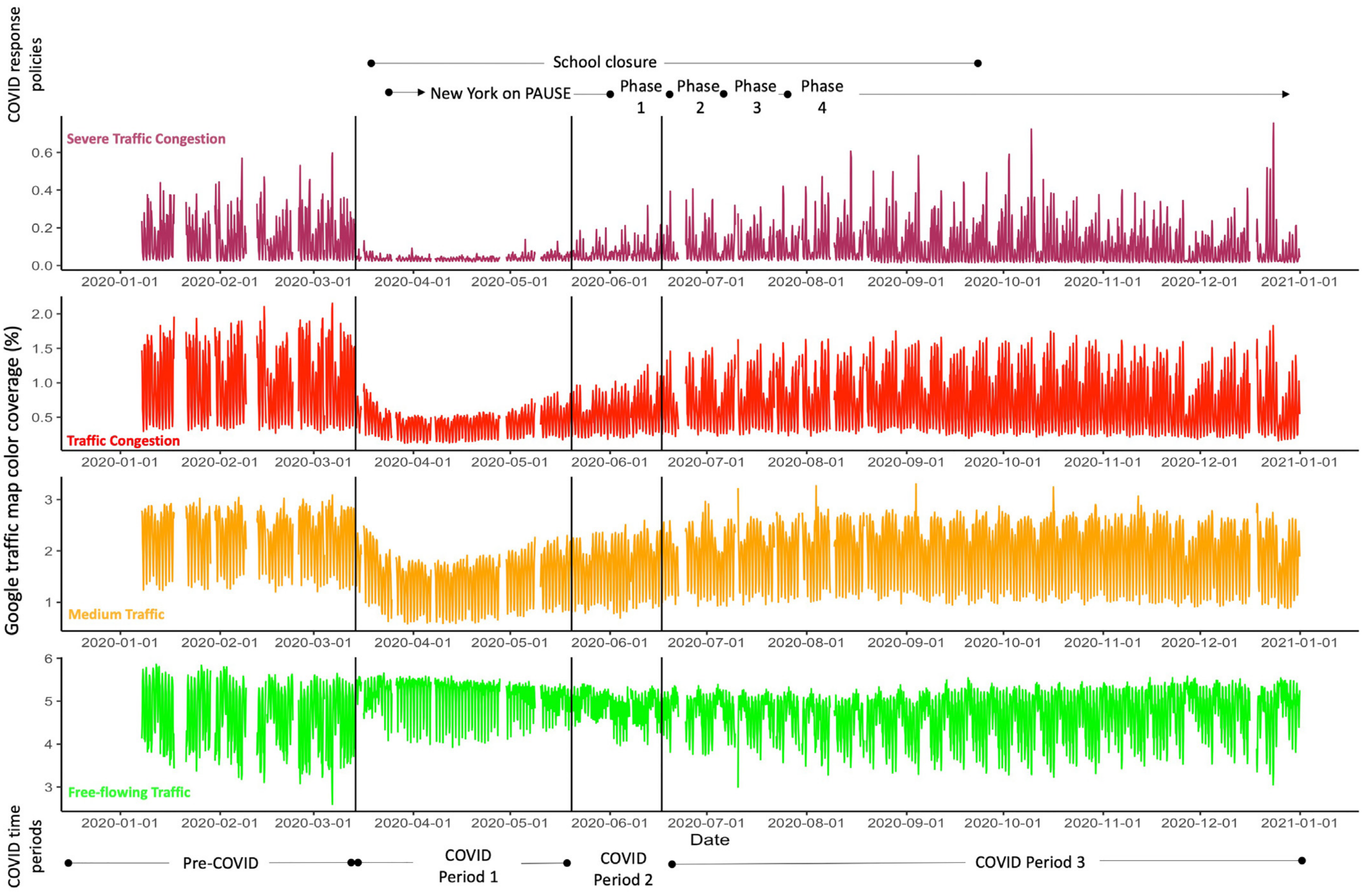

Fig. 2. Time series of the percent of congestion color coverage within Manhattan for the four traffic categories. Vertical black lines delineate COVID time periods for the four separate GAM models, labeled below the bottom x-axis. The timeline of COVID response policies implemented by New York State and city are outlined at the top of the figure.

5 pm, and weekends a clear unimodal peak around 5 pm. However, during COVID Period 1, both weekday and weekend traffic peaks were greatly dampened, and the bimodal weekday distribution shifted to nearly unimodal, becoming very similar to the weekend distribution. During COVID Period 2 and 3 the daily traffic peaks were greater than for Period 1, but still lower than pre-pandemic levels. Even as overall traffic increased during these periods, the weekday distribution remained altered, such that the morning peak was much smaller than the evening peak.

A closer inspection of the GAM splines (Supplemental Fig. 1), including the deviation of the fitted spline from the intercept, further highlight these differences in diurnal traffic congestion. In Panel C of Supplemental Fig. 1, we can see that while the heights of the morning rush hour peak for weekdays remains highest for the Pre-COVID period, for COVID Period 3, the evening rush hour actually has a greater peak than the Pre-COVID period. This shift in traffic from the morning to the evening rush hour results in a diurnal congestion pattern that appears somewhere between the Pre-COVID weekday and weekend distributions.

Table 1
Intercepts a_0 for generalized additive models describing the time series of red traffic congestion coverage T_t (% area) for four time periods during the COVID-19 pandemic.

COVID time period	a_0	p-value of intercept	R^2
Pre-COVID (January 1 – March 13)	0.99	<0.001	0.917
COVID 1 (March 14 – May 19)	0.41	<0.001	0.758
COVID 2 (May 20 – June 16)	0.56	<0.001	0.877
COVID 3 (June 17 – December 31)	0.74	<0.001	0.873

4. Discussion

We present evidence of social-distancing fatigue in Manhattan, NYC, from evaluation of traffic congestion levels during the COVID-19 pandemic. While traffic decreased sharply following the onset of the pandemic and implementation of response policies, levels were already rebounding almost two months before stay-at-home orders (*NY on PAUSE*) were lifted on June 8. Overall, we identified four COVID periods based on traffic congestion patterns. While the dates delineating the COVID periods sometimes lined up with the implementation of official social distancing policies, they did not always. For example, traffic congestion began to plummet on March 14 (Saturday) in advance of school closures effective Monday, March 16, and substantially before NYC bars and restaurants closed in-person service on March 17 and *NY on PAUSE* began on March 22. The time period during which *NY on PAUSE* was in effect spans two different COVID Periods because traffic began to rebound far in advance of the first reopening policy (Phase 1 reopening) which occurred on June 8th. COVID Period 3, when traffic began to stabilize (June 17th), was very close to the Phase 2 re-opening date of June 22 (Fig. 2). We also observe large impacts of the pandemic on the distribution of traffic throughout the day, such that the pre-pandemic bimodal weekday diurnal congestion representing the morning and evening rush hour was dramatically depressed. By September, traffic congestion had rebounded to approximately 75% of pre-pandemic levels.

Dramatic decreases in traffic have been noted in NYC (Schuman, 2020; Bian et al., 2021; Chen et al., 2021) and many other places (Rossi et al., 2020; Patel et al., 2020; Hudda et al., 2020; Parr et al., 2020) in response to the pandemic, including Padova, Italy (Rossi

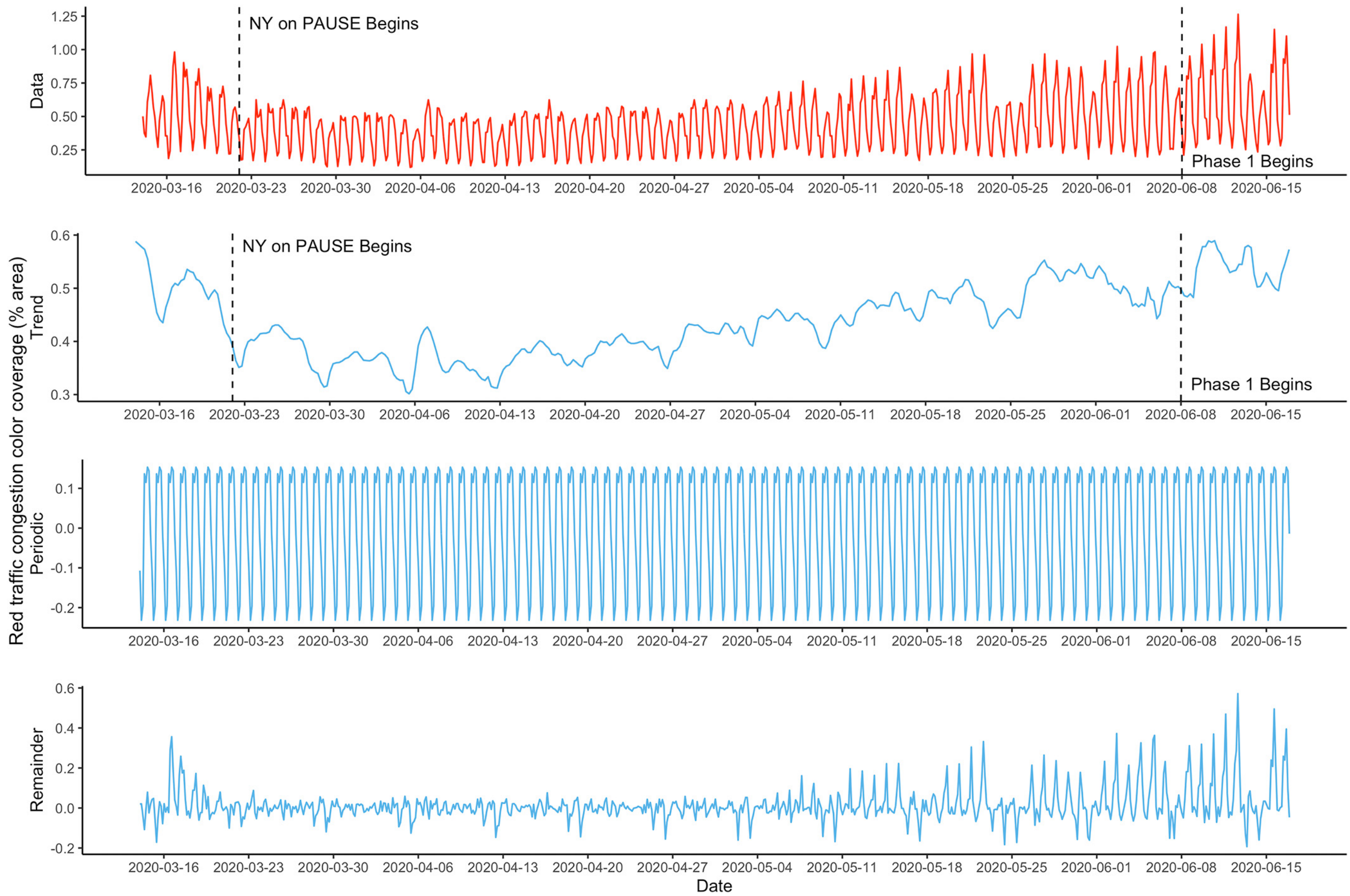

Fig. 3. Time series decomposition of the percent map area covered by red traffic congestion from March 14 to June 16, 2020, with Loess. A time series of the red traffic congestion data is shown in the top panel, while the second panel shows the trend over time, the third panel shows the periodic daily pattern, and the bottom panel shows the remainder (or irregular) components of the time series. Dashed vertical lines indicate dates that policies were implemented to control the spread of the pandemic (left line: *NY on PAUSE*; right line: Phase 1 Reopening).

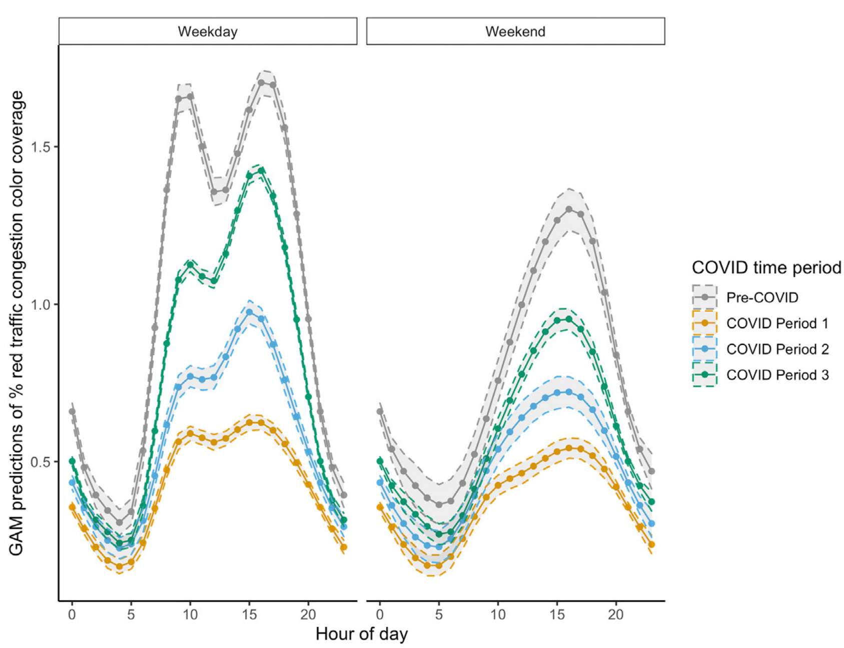

Fig. 4. Diurnal fluctuation of red color coverage (in % area) on the traffic congestion maps for a typical weekday and weekend day (points and solid lines). Typical congestion levels are predicted from the GAM models with 95% confidence intervals (gray shading surrounding by dashed lines), for each COVID time period. Pre-COVID is from January 1 to March 13, COVID Period 1 is March 14 to May 19, COVID Period 2 is May 20 to June 16, and COVID Period 3 is June 17 to December 31.

et al., 2020) and Auckland, New Zealand (Patel et al., 2020). The study in Padova found a decrease in traffic flow (vehicle counts per unit time) in 2020 of approximately 70%, compared to 2018–2017 (Rossi et al., 2020). Similarly, the study in Auckland found a 60–80% decrease in traffic flow following travel restrictions implemented in response to the pandemic (Patel et al., 2020). One analysis of traffic changes in the NYC metro area found reductions of 66% in passenger vehicle traffic the week of March 28–April 3 (Schuman, 2020), while another noted a decrease of 29% following the declaration of emergency and a decrease of 48% just in advance of *NY on PAUSE (*Bian et al., 2021*)*. While the traffic flows reported by these other studies cannot be directly compared to our metrics, our findings were in line with those previously published. We found a 59% reduction in total map area covered by traffic congestion during March 14–May 19, compared to January 1–March 13, and we were able to extend our analysis through the end of 2020. Our findings are consistent with those of Bian et al. (2021), who used a different data source (vehicle flow from 9 bridges and tunnels) and statistical method (change point detection) to also examine social-distancing fatigue in NYC. They found that vehicular traffic began to rebound on April 26, in advance of the 1–5 am closure of the NYC subway system which began on April 30. This is in line with the traffic increase in mid-April we determined through STL analysis. Moreover, Bian et al. identified a 22-day lead time in traffic increase before Phase I reopening (beginning on May 17). May 17 is very close to May 19, the date our COVID Period 1 ended, which consistent with Bian et al. indicates a substantial change from the previous traffic pattern.

In this paper, we use changes in traffic as a measure of human mobility and an indicator for social-distancing interventions. However, an increase in traffic congestion does not necessarily correlate with increased case counts of COVID-19, as a study evaluating correlations between traffic and cases in various cities of South Korea found (Lee et al., 2020). Broadly, we can conceptualize COVID-19 non-pharmaceutical interventions in four categories: face mask mandates, isolation or quarantine (including stay-at-home orders), traffic or travel restrictions (such as limiting travel between cities or counties), and social-distancing (closure of schools or other businesses, or limiting gatherings) (Bo et al., 2021). A review found that social-distancing was the most effective single non-pharmaceutical intervention, while combining social-distancing with at least one other intervention was even more effective (Bo et al., 2021). Traffic congestion can be thought of as an indicator for three of these intervention groupings (all but mask mandates), as human mobility is a component of isolation or quarantine, traffic or travel restrictions, and social-distancing. As such, it makes sense to hypothesize that increased congestion may correlate with increased opportunity for SARS-CoV-2 transmission. However, increases in traffic congestion may also be an indicator of a switch in transportation methods in response to the pandemic; studies have documented dramatic decreases in use of public transportation in NYC (Sy et al., 2020) and metro areas in Sweden (Jenelius and Cebecauer, 2020). It is possible that individuals who otherwise would have used public transit such as subways or buses are now relying more heavily on private or shared vehicles to reduce their chance of exposure, as was found in Canada (Labonté-LeMoyne et al., 2020).

There are many potential reasons that mobility may increase in advance of the release of stay-at-home orders. Specific to the NYC area, after a few weeks of stay-at-home orders, people may have increased their travel outside the city to participate in outdoor activities. For example, NYC did not fully reopen its beaches until July 1 (City of New York, n.d.). Beaches were open for walking, but not for gathering, sunbathing, or swimming, while neighboring states, including New Jersey and Connecticut, never closed their beaches (Connecticut) or reopened them far earlier (New Jersey: May 22) (ABC 7 New York, 2020). This may have contributed to the increase in vehicle traffic we observe as the weather warmed in advance of NYC's Phase 1 reopening, e.g., if individuals used private vehicles or ride share services rather than public transportation to go to beaches in New Jersey or Connecticut. More generally, there are a number of other reasons that social-distancing fatigue may occur. First, it is more difficult for individuals with lower socioeconomic status to reduce their mobility, especially long-term, because (1) their savings or resources may be used up within a few weeks or months (Martin et al., 2020), (2) they make up a larger share of essential workers (Lou et al., 2020; Dingel and Neiman, 2020), and (3) they may not be able to reduce essential trips like grocery store visits by purchasing larger amounts of food at once (Wolfson and Leung, 2020), a problem likely to be exacerbated as stay-at-home orders were extended. Second, the pandemic has been particularly challenging for single parents (Fu and Zhai, 2021), who may have struggled to social-distance while navigating childcare and making a living. Third, the pandemic has had negative impacts on mental health (Marroquín et al., 2020; Conroy et al., 2021), potentially increasing people's need for social support and decreasing their ability to remain socially distant, especially as time goes on. All of these reasons could have contributed to social-distancing fatigue in advance of Phase 1 reopening, as New Yorkers became less and less able to adhere to social-distancing guidelines.

Understanding changes in traffic congestion during the pandemic is useful not only as a proxy for human mobility, but also for implications on large-scale traffic interventions that may be implemented in the future. For example, in 2019 New York City became the first American city to approve a congestion pricing policy (Durkin and Aratani, 2019), with implementation scheduled to begin in early 2021 (although this was delayed). The large-scale traffic disruption that followed implementation of *NY on PAUSE*, however, may be useful in informing what kinds of changes in traffic patterns could reduce congestion. As we saw in COVID period 1, traffic congestion can be reduced both by depression of overall traffic and by dampening the bimodal diurnal congestion driven by weekday rush hour.

In this paper, use of STL analysis allowed for clear identification of the increasing trend in traffic congestion, while use of GAM models allowed us to account for the changing within-day distribution of the congestion data over the course of the pandemic. These methods allowed us to identify the presence of social-distancing fatigue and to describe traffic changes by hour, demonstrating a clearer picture of the impact of the pandemic on traffic in NYC. This information is useful not only as a proxy for tracking human mobility, but also for understanding how large-scale travel restrictions can impact traffic patterns and congestion overall. Additionally, by using crowd-sourced, publicly available data at high temporal and spatial resolution, we were able to obtain traffic coverage for all of Manhattan in near real time. This is particularly advantageous for evaluating changes that occurred during the pandemic, when government collection of data may have been limited due to closures and emergency response, and for future emergency response management.

Out study has some notable limitations. First, we include a fairly limited geographic area (the borough of Manhattan, NYC), and thus results of our study may not be generalizable to other areas. However, studies in other cities also find dramatic decreases in traffic, on a similar scale as that reported here (Rossi et al., 2020; Patel et al., 2020; Parr et al., 2020). Second, our data source does not allow for disaggregation of passenger vehicles and trucks, which were likely differentially impacted by responses to the pandemic (as trucking operations may be considered essential businesses). Studies in NYC (Gao et al., 2020) and Somerville MA (Hudda et al., 2020) have found decreases in both vehicles and trucks, though the decrease was substantially less for trucks. Third, we do not disaggregate traffic changes by neighborhoods, and thus do not report variation in congestion changes within Manhattan. We recommend that future studies describe and evaluate these potential differences.

5. Conclusions

Using highly temporally resolved, crowd-sourced traffic congestion data, we describe changes in traffic congestion in Manhattan, NYC, during the COVID-19 pandemic. We report dramatic declines in traffic congestion during the initial stages of the pandemic and implementation of stay-at-home orders, followed by rebounds in congestion nearly two months before stay-at-home orders were reversed, evidence of social-distancing fatigue. Additionally, we describe changes in diurnal traffic congestion patterns for weekdays and weekends, by hour, for four time periods during the pandemic. This data can be used to inform human mobility changes during the current pandemic, in planning for responses to future pandemics, as well as in understanding the potential impact of large-scale traffic interventions such as congestion pricing policies.

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CRediT authorship contribution statement

MH, MEM, and JAS conceptualized and guided the study. MH obtained data. JAS conducted analysis and wrote the manuscript draft. YN revised and edited analytic scripts. All authors read, edited, and approved the final manuscript.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Supplementary material

Supplementary data to this article can be found online at https://doi.org/10.1016/j.scitotenv.2021.148336.

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