Quantifying the Traffic Impacts of the COVID-19 Shutdown

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Abstract: The coronavirus disease (COVID-19) pandemic has significantly disrupted transportation and travel patterns across the US and around the world. A significant driving factor in the significant reduction in travel in the US was the declaration of varying state-, county-, and city-level stay-at-home orders with varying degrees of reduction. However, it is still not clear how significantly any one of those orders contributed to the reduction in travel. This article looks at continuous count data from the Minneapolis–St. Paul, Minnesota, area to quantify the disruption in terms of reductions in traffic volume as well as the abnormality of the disruption to travel patterns. A nearly 50% reduction in total traffic volume is found, and regional trends both in reductions and the gradual recovery toward normal travel patterns are identified. Furthermore, key dates are identified that led to significant reductions in travel, and this disruptive event is compared with other significantly disruptive events in Minnesota for context. It is found that although the stay-at-home order was a significant milestone in the fight against COVID-19, traffic volumes had already reduced significantly before the order went into effect, and traffic volumes had recovered significantly before the order expired. These findings will be helpful in understand the impact of stay-at-home orders on future outbreaks of COVID-19 or other pandemics. **DOI: 10.1061/JTEPBS.0000527.** *© 2021 American Society of Civil Engineers.*

Introduction

In December 2019, a novel coronavirus (SARS-CoV-2) that causes COVID-19 was first identified in Wuhan, Hubei Province, China. The virus quickly spread through provinces in China and caused major travel disruptions during the Spring Festival celebrations in late January and early February. By late February, there were COVID-19 outbreaks in multiple countries, and the World Health Organization (WHO) declared COVID-19 a global pandemic in mid-March 2020. Although the COVID-19 pandemic has disrupted daily life in many aspects, one way in which COVID-19 has significantly altered life is the disruption it has caused to both long-distance travel and local transportation. This is a result of reduced travel demand, an increase in telecommuting or working from home, and a patchwork of governmental directives such as stay-at-home orders that were issued by local, regional, and national governments.

It is clear that COVID-19 has caused a substantial disruption, but it is still unclear how significant the change in travel patterns has been, and how substantial this shift has been when compared with other disruptive events. Furthermore, the use of differing degrees of stay-at-home orders (e.g., complete stay-at-home order versus allowing some businesses to reopen) has influenced travel demand at every phase of the COVID-19 pandemic. Understanding how differing directives have influenced travel patterns, and how slowly, over time, people return to normality without any substantial change in directive or legislation, will help allow better responses to future outbreaks or resurgences of the COVID-19 virus or other similar pandemics.

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Understanding the degree of disruption and corresponding resilience of urban transportation networks with regards to disruptive events has been an area of significant interest. Many efforts focused on the transportation network disruption caused by natural events such as extreme weather (Chan and Schofer 2016; Glass et al. 2018; Gori et al. 2020; Shen and Aydin 2014) or climate change (Markolf et al. 2019; Pregnolato et al. 2017), whereas others looked at the resilience of transportation networks to such events. For example, looking at the transportation system level, Donovan and Work (2017) used the Mahalanobis distance (Mahalanobis 1936) to quantify the degree abnormality of traffic before, during, and after Hurricane Sandy in New York City, New York, and used this to identify when the traffic was most anomalous. Others have focused on identifying anomalous traffic conditions at the individual link level using various video detection systems (Athanesious et al. 2019; Dong et al. 2010; Li et al. 2020). However, when it comes to analysis of a transportation network, these studies all consider a supply-side disruption, i.e., a reduction in network capacity. In the case of the COVID-19-related shutdown, the disruption has primarily been a demand-side disruption where fewer people travel as a result of stay-at-home orders. Therefore, the same network analysis tools are used to understand how transportation networks respond to major disruptions, and these methods are applied to the demand-side disruption at the start of the COVID-19 shutdown.

The COVID-19 pandemic has already been shown to have significantly altered transportation and travel behavior. For example, Beck and Hensher (2020) studied household travel during the initial travel restrictions in Australia and found a decrease in household travel, and Abu-Rayash and Dincer (2020) unsurprisingly found a substantial decline in global air travel during the COVID-19 pandemic. The COVID-19 pandemic has inspired much academic research as engineers, state and local governments, and researchers try to understand how the pandemic has changed, and will continue to change, travel patterns (Aletta et al. 2020; Lee et al. 2020; Parr et al. 2020; Hendrickson and Rilett 2020). In many cases, this has led to better air quality in the short term (Xiang et al. 2020). Looking at pandemics more broadly, others have found significant disruptions to transportation networks in other pandemic outbreaks (Xu et al. 2019). As mentioned previously,

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although many natural disasters cause a disruption to the transportation network supply by reducing road and airport capacity, the COVID-19 pandemic has caused a disruption to the demand for transportation.

With that in mind, this article uses continuous count data from the city of Minneapolis, Minnesota, as a case study to quantify the abnormality of traffic conditions during the COVID-19 pandemic. Specifically, the authors are interested in measuring how likely a particular traffic volume is based on historic fluctuations in traffic volumes. This study investigates how each individual change to the state- and city-level stay-at-home order influenced travel behavior, as well as how the rising COVID-19 infection level within the state contributed to the travel disruption. This article discusses and implements statistical tools to quantify degree of abnormality, and compares the abnormality of the events with other significantly disruptive events. There is also an investigation into how different regions (e.g., downtown, suburbs, and rural areas) were influenced differently by the pandemic and resulting stay at home orders. This provides an early analysis into how the COVID-19 pandemic and associated government orders affected vehicular travel. The insight into how the transportation network responds to different mechanisms will be valuable in any future outbreaks of COVID-19 or other similar viruses.

The remainder of this article is outlined as follows. First, different methods for traffic data detection are discussed, followed by a discussion of quantifying abnormality in traffic data based on these measurements. Next, a case study using data collected in Minnesota is introduced, and regional trends in the data during the COVID-19 pandemic are discussed. The experimental data are compared with previous disruptive events. Finally, it is concluded that the COVID-19 pandemic has been severely disruptive to travel patterns, with the degree of disruption and rate of recovery differing by geographic region.

Traffic Detection

To understand how the COVID-19 pandemic has influenced travel, the authors are interested in identifying traffic volumes on individual roadways. Traffic detection has been an area of research for many decades, with many technologies developed and deployed. Traffic detection techniques generally can be categorized as one of three types: (1) in-pavement; (2) overhead detectors; and (3) mobile detectors.

All three types of aforementioned methods provide accurate traffic detection (Riveiro et al. 2017; Mercader and Haddad 2020; Cherrett et al. 2005), and the anomaly detection techniques discussed subsequently could be applied to any of them. However, because they are the most prevalent detectors installed in urban infrastructure, the focus of the methods discussed, as well as the analysis presented in this article, will focus on vehicle counts, or continuous count data. These data provide individual vehicle counts at particular fixed locations in the infrastructure over a short time interval (e.g., 1 min or 1 h). These data can be used to assess the usage and performance of the roadway infrastructure and detect anomalous traffic conditions, as discussed next.

Description of Traffic Data

The data set used in this analysis was collected from the Minnesota Department of Transportation (Minnesota DOT), which collects traffic volume (number of vehicles observed) and speed information from a series of detectors in the Minneapolis, Minnesota, and surrounding areas. For this analysis, data from 300 detectors on Minnesota roadways were utilized. Only detectors that have valid data for the duration of the study period (January 4, 2015–July 18, 2020) were used, meaning that there are no missing data. This is necessary to eliminate detectors that are no longer operational or are too new to the system to provide reliable historical traffic counts. However, this data set provides combined counts for passenger vehicles and trucks and does not allow for observing different trends for different vehicle types.

Traffic volume data collected during the first 28 complete weeks of each year (for 2020, this is from January 5 to July 18) are used, which corresponds to the time frame of interest relative to COVID-19. Throughout this article, the 2020 data are referred to as the subject data set, and the 2015–2019 data are called the baseline data set. Further filtering was done on all chosen detectors to eliminate those which had intermittent down times in the observed time frame, which resulted in a reduced number of sampled detectors of 262. This filtering of detectors with intermittent downtime was needed to ensure the result were not skewed by large gaps in the data for some detectors. Fig. 1 shows the detectors used in this study and gives a sense for the geographical area covered and distribution.

A small subset of the subject data set is presented in Table 1 to provide an example of how the data are stored. The data contain the average number vehicles observed for each 30-min time period in the data set. The data were provided in 30-min increments, and therefore this is the highest granularity that can be observed.

Quantifying Traffic Abnormality

To quantify the traffic abnormality, two separate statistical metrics are considered: percent change relative to prior years and normalized deviation from the mean relative to prior years. For the purpose of these metrics, the data will be examined in terms of weekly averages, Sunday to Saturday, to eliminate the day-of-the-week-dependent effects such as the presence of increased worker commute traffic on weekday measurements. Considering the weekly averages allows for observing the overall traffic patterns resulting from COVID-19.

Percent Change from Prior Year

By computing the percent change in traffic volume at a particular detector with respect to the same day of the week the previous year, a simple estimate can be obtained for how substantially traffic volumes have been affected. This is computed as follows:

$$\Delta_d(t) = \frac{V_d(t) - V_d^b}{V_d^b} \tag{1}$$

where $\Delta_d(t)$ = percent change in traffic volume from the historical baseline traffic flow observed at detector d on day t; $V_d(t)$ = traffic volume observed for detector d on day t being considered in the subject data set; and V_d^b = baseline mean volume for detector d that has been observed in the past. Eq. (1) is computed for each sensor at each point in time and then averaged across all sensors in the study area. Thus, one can also compute the distribution in volume change for each data point.

Percent change from prior year provides a metric for comparison between 2 years. Although there is no theoretical maximum value, there is a practical maximum value because a particular roadway cannot go beyond the capacity of the road, which is generally assumed to be roughly 2,000 vehicles per hour per lane. The minimum value that the percent change can take is −100%, which

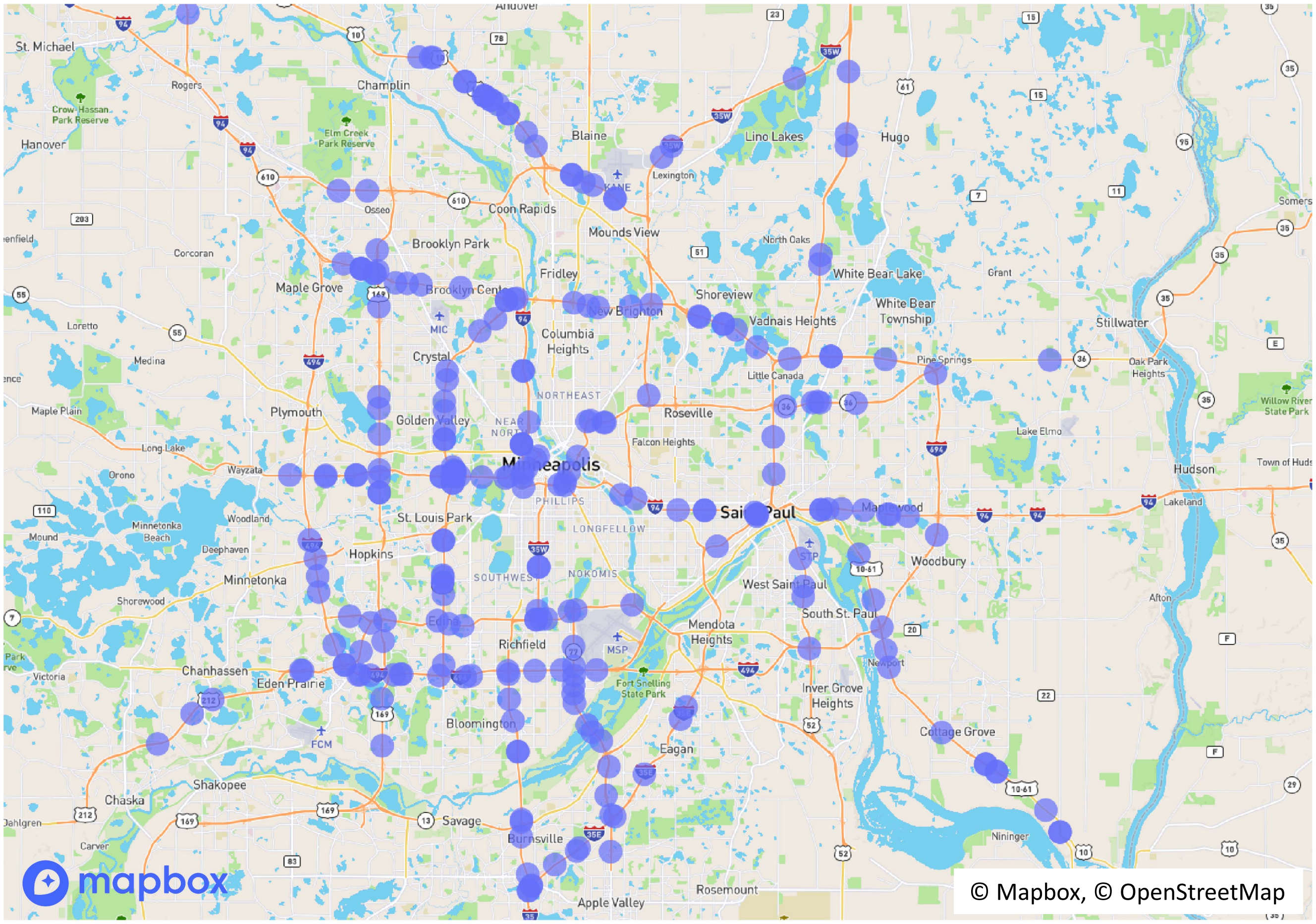


Fig. 1. Locations of the Minnesota DOT traffic detectors used to analyze traffic volume abnormality and response to COVID-19-related government orders. (Map data from Mapbox and OpenStreetMap and their data sources. To learn more, visit https://www.mapbox.com/about/maps/ and http://www.openstreetmap.org/copyright.)

Table 1. Example of subject volume data used in this article, with average being the mean number of vehicles observed by that detector for each sample period (30 min) on each date

Detector ID	Date	Average
100	January 5, 2020	396.6522
100	January 6, 2020	592.9130
100	July 18, 2020	383.3912

corresponds to no traffic being observed. This metric helps to identify trends in the traffic volume patterns, but it does not conclusively signify an anomaly because it does not take typical traffic volume variation into account.

Normalized Deviation

To quantify the abnormality in the network compared with the historical baseline data set, the average normalized deviation from the mean (i.e., z-score) of the detectors is also used, allowing the percentage change in traffic volume to be contrasted with the standard deviation observed in the baseline historical data. The formula to compute the normalized deviation $Z_d(t)$, where d is a specific detector and t is a specific day, is provided in Eq. (2)

$$Z_d(t) = \frac{V_d(t) - \mu_d^b}{\sigma_d^b} \tag{2}$$

where $V_d(t)$ = traffic volume observed for the detector and day in the subject data set; and μ_d^b and σ_d^b = volume mean and volume standard deviation, respectively, for the detector in the baseline data across all days in the historical baseline data set. The historical baseline data set contains only the date range in the subject 2020 data set.

This metric allows for examining how abnormal the fluctuations in traffic volume caused by COVID-19 are. Importantly, this metric provides a detector-level measurement of traffic abnormality. Thus, this metric, as well as the percentage change metric, are utilized to identify regional trends in the traffic effects of COVID-19.

For a particular measurement or observation, the normalized deviation tells how many standard deviations the observed measurement is. Values below zero indicate that the measurement is lower than average, whereas values above zero indicate the measurement is larger than average. Although there is no theoretical maximum or minimum value for the normalized deviation, values of greater than 3 or less than −3 are considered to be abnormal.

Data and Discussion

In this section, the discussed measures of traffic volume and abnormality to are applied continuous count traffic flow data collected in

Table 2. Subject data set volume statistics across all detectors and dates

Property	Value (vehicles)
Median	379.24
Mean	411.10
Maximum	2,722.35
Standard deviation	255.11

the state of Minnesota. A first view is thereby presented of how the different stay-at-home orders in Minnesota influenced traffic volumes both in urban and rural areas of the state.

Data Preprocessing and Filtering

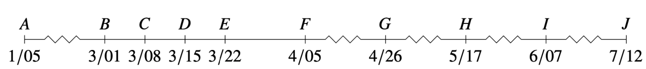
All data were cleaned through a preprocessing and filtering step to identify which sensors were missing data at any point during the study period (e.g., due to faulty sensors). This preprocessing included analysis of the data set to identify any time periods where data were missing. Sensors that had significant amounts of data missing were omitted from the analysis, and data were interpolated for sensors that had brief outages. A summary of average statistics for all sensors in the cleaned data is presented in Table 2.

General COVID-19 Trends in Minneapolis

To analyze the data on traffic volume, the trends need to be compared with the timeline of events involving COVID-19 in Minneapolis. The timeline in Fig. 2 gives a simple representation of which weeks in which different government orders and COVID-19 milestones occurred. Thus, the timeline shows the start of the week after each event occurred. Specifically, the stay-at-home order declared on March 25, 2020, required all nonessential workers to work from home and only allowed essential travel, but all nonessential businesses had already been closed. When the stay-at-home order expired on May 18, nonessential business was permitted again, and outdoor dining was permitted at restaurants, but employees who were able to work from home were required to continue working from home. On June 10, Minnesota entered Phase 3 of the reopening, which allowed for limited indoor dining at restaurants.

When comparing these changes in state-level policy and significant case number milestones with traffic trends, it is important to consider that some significant events occur toward the end of the week they are in, and so the effects may not be fully seen until the following week.

With this timeline in mind, the authors are particularly interested in significant changes to traffic volume at each of these milestones to see how the traffic trends reacted, as well as the characteristics with which traffic returned to normal levels.



A: Start of our analysis
B: First case of COVID-19 in Minnesota on the 6th of March
C: State of emergency is declared on the 13th of March
D: Schools are closed on the 15th of March, all non-essential businesses ordered to close on the 16th of March, first death in Minnesota due to COVID-19 on the 21st of March
E: Governor announces stay-at-home order on the 25th of March
F: Stay-at-home order extended on the 8th of April
G: Stay-at-home order extended for second time on the 30th of April
H: Stay-at-home order expires on the 18th of May
I: Phase 3 of Minnesota reopening plan begins on the 10th of June
J: Last week we analyzed, emergency order still in place for Minnesota

Fig. 2. Timeline of COVID-19 events in Minnesota. All listed events occur the listed date or following 6 days.

Abnormality of Traffic during COVID-19

From the subject data set, one can observe the relative percent change in traffic volume seen in Fig. 3(a) when looking at the average of all detector. Data are only provided for the points in Fig. 3(a), and the bars represent one standard deviation in reduction across all sensors in the study area. It can be seen from these results that the volume fluctuated between −5% and 5% up through the week of March 1, in which the first COVID-19 case was recorded. The start of a decrease in traffic volume is observed in the week of March 8, when the state of emergency was announced in Minnesota, but remains within the ±10% range, likely due to the start of that order occurring towards the end of the week. Following these events, one can see the traffic volume drops in the city to levels of approximately 50% of the baseline expected traffic volume by the week of March 29, at which time the full stay-at-home order went into effect. The distribution of the reduction widens after mid-April, when traffic volumes began to rise again, indicating that some areas saw an even larger reduction in traffic, whereas others were less affected.

Considering this in terms of the z-score averaged from all sensors sampled, presented in Fig. 3(b), one can see that this dip translates to a full two standard deviations, meaning the traffic volume decreases are well outside the expected typical variation in magnitude seen in the baseline data.

Following the week of March 29, the downward trend in traffic volumes begins to reverse, maintaining a steady recovery trend of approximately 3% per week, reaching an apparent plateau from the week of June 21 at 10%−15% below the baseline traffic volume, which is small enough to be within half a standard deviation in typical traffic volume fluctuations. In other words, by June 21, the traffic volume, although still affected, had stabilized at roughly 10% below typical traffic volumes.

With this, one can describe the magnitude of the effects on traffic volumes that COVID-19 and the government orders have had, as well as how unlikely these are to be due to regular volume variations based on previous years' data. The COVID-19-related shutdown reduced traffic volume on average throughout the city by 50%. However, these effects proved to be only temporary, after which the traffic volume began to recover at a slow but steady pace. Although the decrease in traffic volumes coincides with the enactment of the stay-at-home order in Minnesota, one can observe that this recovery in traffic volumes occurred independently of the repeal of the stay-at-home and reduced operation orders that were put in place.

The timeline in Fig. 2 and reduction in traffic volume in Fig. 3 indicate that most significant changes in traffic volume occurred after the first case of COVID-19 was detected in Minnesota (Point B) as well as the state of emergency being declared in Minnesota (Point C). By time the governor issued a stay-at-home order in Minnesota (Point E), traffic volumes had already dropped significantly from the initial traffic volumes. Traffic volumes began slowly climbing again when the stay-at-home order was extended (Point F), and continued to climb at a steady rate through the second extension of the stay-at-home order (Point G), as well as the end of the shelter-in-place order (Point H). This shows that, although important in influencing traffic volumes, the stay-at-home order was not the primary factor influencing traffic volumes. Instead, it is possible that fear of COVID-19, or some other factor, was the primary driving factor in reducing traffic volumes in Minnesota. However, it is important to point out that the data count individual vehicles and do not disaggregate between passenger vehicles and trucks. Therefore, although passenger vehicle volumes decreased, it is not known how the increase in trucking during the COVID-19 pandemic influenced these traffic counts.

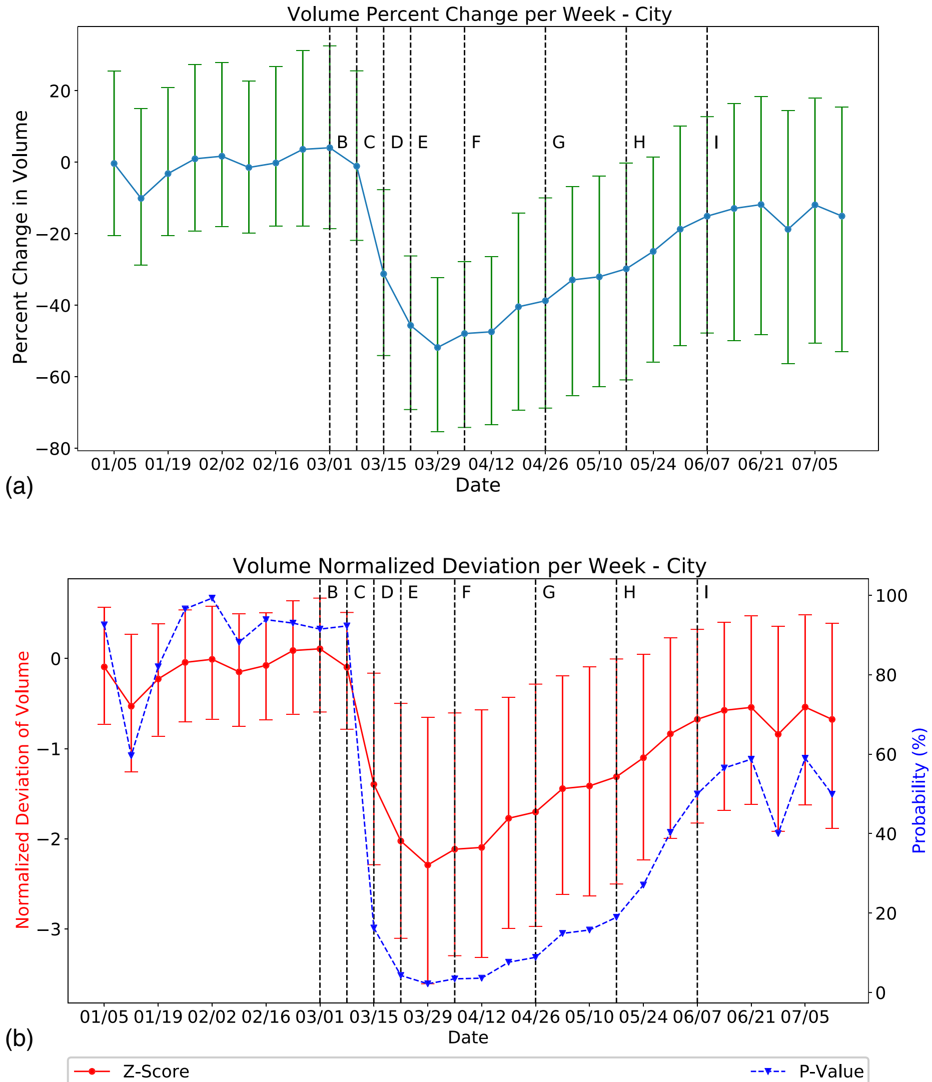


Fig. 3. Percent change in traffic volumes and normalized deviation of traffic volumes from expected volume (z-score) during the COVID-19 pandemic in 2020: (a) percent change in traffic volume from baseline traffic volumes, averaged for all detectors, where bars represent one standard deviation in measurements across all sensors in the study area; and (b) normalized deviation from typical traffic volumes during baseline during COVID-19, averaged for all detectors.

Regional Trends in COVID-19 Data

Next, regional variation in traffic volumes as a result of the COVID-19 pandemic and corresponding state mandates such as the stay-at-home order and partial stay-at-home order are investigated.

Traffic Abnormality during COVID-19 in the Urban Core

Fig. 4 shows that the general trend in traffic volume up to the end of March, excluding several outliers, appears to be similar across the different detectors. Following that, however, the detectors begin diverging into two distinct recovery groups, one group recovering at roughly the rate described previously of 3% recovery per week, and the other trailing behind at a much slower rate of approximately 1.5% per week. Both these groups appear to respond in similar ways at the earlier times of interest, including both before the first recorded case of COVID-19 in Minneapolis, as well as when the volume first decreased in March. However, there are visible differences among several groups of detectors in their rate of recovery back toward normal values after reaching the lowest observed percent change.

To get a better understanding of these data and to be able to identify any spatial patterns in where these slow-to-recover detectors are located, the data are plotted geographically in Fig. 5 with each circle indicating the percent change in traffic volume from the baseline traffic data at a particular sensor (located at that geographic location). Although these data are continuous in time, a sampling of four distinct time periods in the COVID-19 timeline are plotted in Fig. 5. At the beginning of March, prior to any government orders, the general distribution for the traffic volume appears to be mostly in line with the baseline data set. There is a small section of detectors that already have decreased traffic volume, likely due to proximity to the Minneapolis St. Paul International (MSP) Airport, as well as a section with slightly elevated traffic in the northeast of the city.

Fig. 5(b), which represents the lowest traffic volume, shows a regional trend in terms of how significant of a volume reduction is observed. Specifically, the southwest of the city sees the 50% decrease in volume identified previously; however, the northeastern side instead sees a closer to 30%–40% decrease in volume, with a

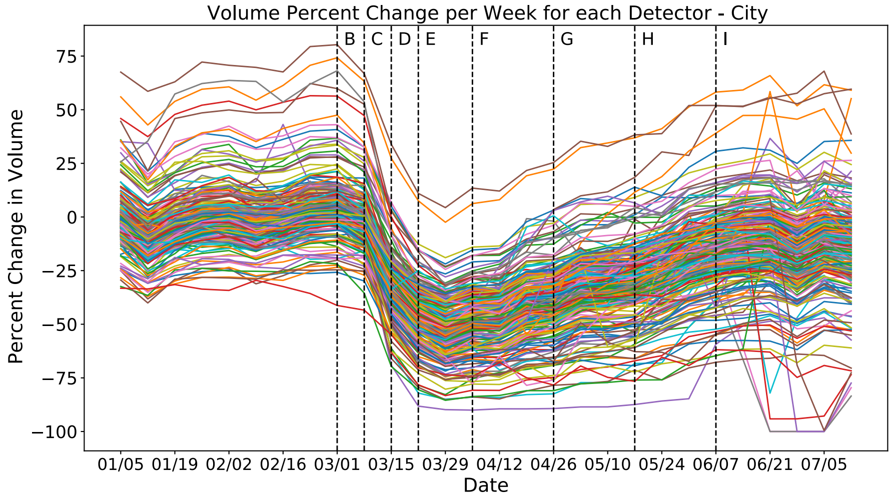


Fig. 4. Percent change in traffic volume by detector.

small section even maintaining close to baseline levels of traffic volume. It is possible that this smaller reduction in traffic volume in northeast Minneapolis is a result of the many industrial facilities in that part of the city, which continued to operate even during the COVID-19 shutdown and stay-at-home order.

Finally, looking at the distribution of traffic volume impacts during the recovery, one can see that the regional distribution of traffic volume change generally follows the same pattern, with the southwest remaining 20%–40% below prepandemic traffic volumes, and the northeast of the city recovering more rapidly and seeing traffic volumes 10%–0% below the baseline. This is likely because of the predominately suburban makeup of the southwest of the city, where many professionals continued to work from home even after the stay-at-home order ended. This recovery is visualized in Fig. 6, where the percent recovery from prepandemic traffic volume levels is plotted for July 2020. This highlights the divide in the recovery rates between the two regions of the city.

Traffic Abnormality in Rural Areas

In contrast to the urban traffic detectors, data were also collected from 15 detectors along Interstate I–94 in a rural part of the state near St. Cloud, Minnesota. The data from these detectors were preprocessed using the same procedure as for the remaining data, and these data were not included in the baseline data for the urban analysis. The detectors, and their volume percentage shifts relative to the baseline data for the same detectors, can be seen mapped in Fig. 7. Fig. 8 shows that the traffic volume prior to COVID-19 was roughly in line with that observed in the greater metro area, and the timing of the responses were similar as well, with a initial decrease in the week of March 8, followed by a continuous drop until reaching just 50% of the baseline data values.

The data demonstrate that this location reached its minimum traffic volume slightly later than the greater metro area, on March 29 instead of March 22. Starting in the week of May 5, a similar steady increase in traffic volume is observed, although the rate of increase appears to be closer to 4%–5% per week, which implies these rural areas increased more quickly than the urban parts of Minnesota. An interesting observation is that the traffic volume actually appears to have exceeded the traffic volume prior to March, reaching what appears to be a plateau at a 0%–10% elevation from the baseline data. However, only a limited amount of data were collected at this location, and therefore additional data would need to be collected to make broader claims about how traffic in rural and urban areas responded differently to the COVID-19-related travel restrictions.

Statistical Significance of Disruption

This study tests the hypothesis that the traffic volume is significantly different from the baseline data against the null hypothesis that COVID-19 did not cause a statistically significant disruption in traffic volumes. This analysis is conducted on a day-by-day basis, and the resulting probability of observing these particular traffic volumes on a particular day under the assumption that traffic volumes are the same during the COVID-19 pandemic as they were in the baseline data set is plotted in Fig. 3(b). The vertical axis on the right of the figure gives the corresponding probability for the null hypothesis that the traffic volumes during COVID-19 are drawn from the same distribution as the traffic volumes in the baseline traffic data against the alternate hypothesis that traffic volumes are statistically different.

Based on the results presented in Fig. 3(b), the probability of observing such traffic volumes under the null hypothesis that traffic volumes under normal circumstances goes below 95% beginning the week of March 8, when the state of emergency was declared in Minnesota and before the stay-at-home order was enacted. Traffic volumes remained statistically significantly low compared with typical traffic volumes for the duration of the analysis period despite the significant rebound in traffic volumes observed in June and July.

Comparison with Past Disruptive Events

To identify how significant these effects are compared with other events that have caused traffic disruptions, historic traffic data are also examined to put the COVID-19-related disruption into perspective. The events considered are part of the variability observed in the baseline data considered for the COVID-19 impacts analysis. Specifically, the authors consider the disruptive traffic events that occurred when Minneapolis hosted the Superbowl football event and the time before and after the game during the time period from January 14 to February 24, 2018, as well as several major snow events during that time period. Traffic volumes during this event are examined on a day-by-day basis in Fig. 9. This figure shows the percent change in traffic volume from the corresponding day of the week in the baseline data set to account for day-of-week

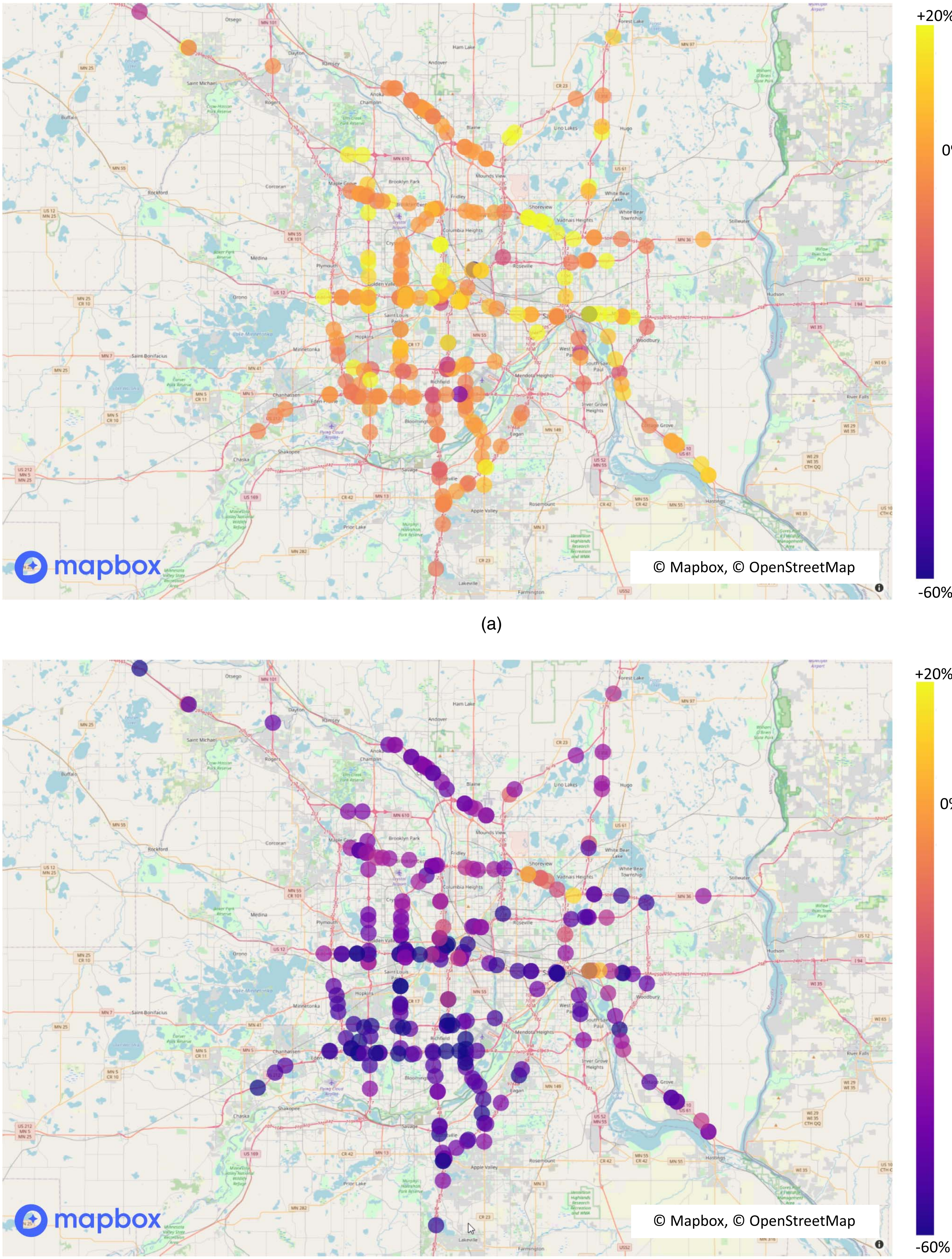
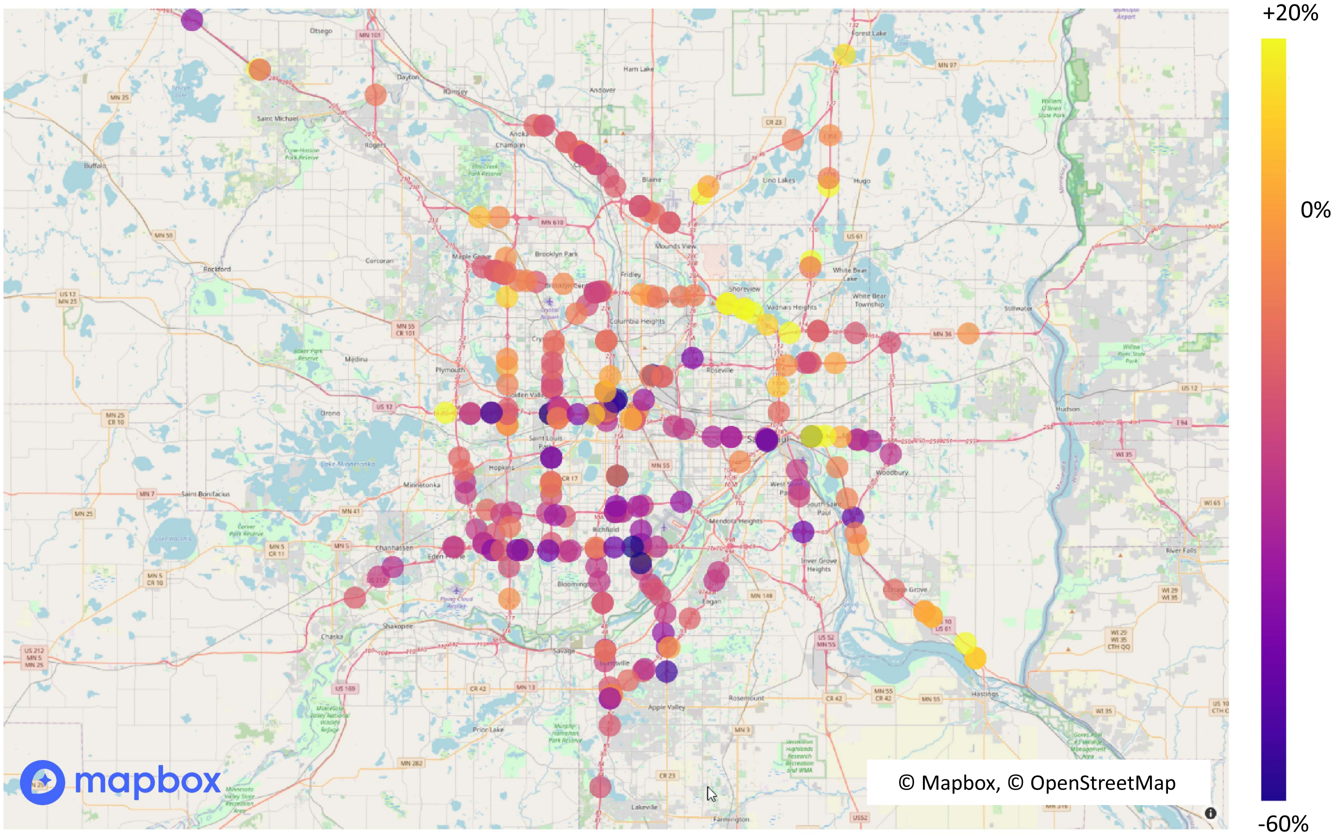
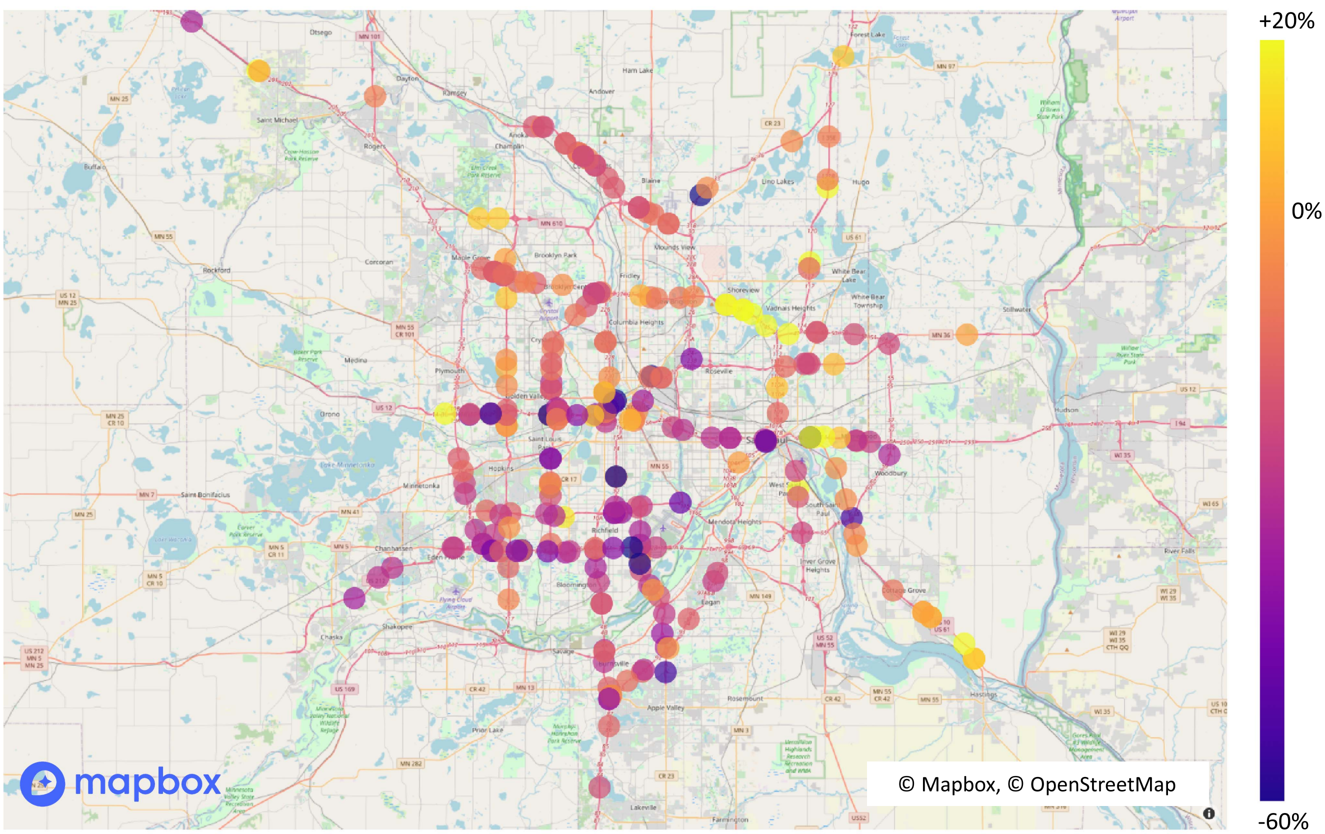


Fig. 5. Minneapolis percent volume change by location: (a) March 1, 2020; (b) March 22, 2020; (c) June 7, 2020; and (d) July 12, 2020. (Map data from Mapbox and OpenStreetMap and their data sources. To learn more, visit https://www.mapbox.com/about/maps/ and http://www.openstreetmap.org/copyright.)



(c)



(d)

Fig. 5. (*Continued.*)

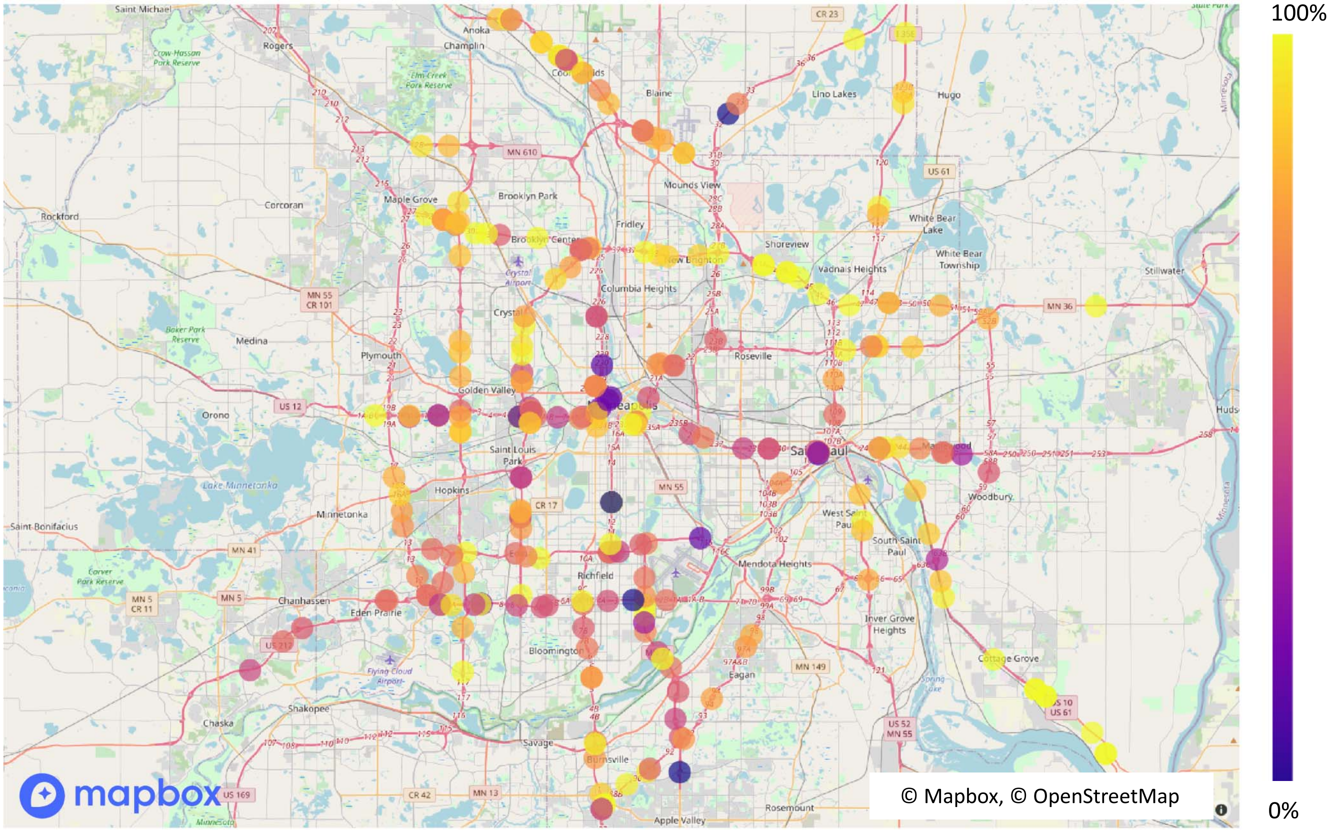


Fig. 6. Percent by which traffic volume has recovered at July 12, 2020, from typical minimum to typical maximum volume levels in subject data set, with the scale ranging from 100% (fully recovered) to 0% (not recovered from COVID-19 levels). (Map data from Mapbox and OpenStreetMap and their data sources. To learn more, visit https://www.mapbox.com/about/maps/ and http://www.openstreetmap.org/copyright.)

traffic volume fluctuations. Fig. 9 shows an approximately 0%–10% increase in traffic volume compared with the previous year, similar to what was observed in pre-COVID-19 results in preceding sections.

Four significant reductions in traffic volume (defined as dropping below the norm from the baseline data) can be observed; these occurred on the January 22, as well February 3, 19, and 24. The reduction on February 3 corresponds with the Superbowl the following day, with a peak reduction in traffic volume of about 5% compared with the up to 50% reduction observed in the COVID-19 effects. The other three events in this figure do appear to present a much more significant effect on the traffic volume, ranging from 10% to 20%. This reduction in travel corresponds to inclement weather events on January 22, February 19, February 22, and February 24, 2018, including snow and cold weather reaching as low as −20°F (−29°C). With this perspective of a major disruptive event such as hosting the Superbowl in Minneapolis, the data show that from the perspective of traffic reduction, COVID-19 and the corresponding shutdown has been roughly five times as disruptive as the Superbowl on a single day. Yet the COVID-19-related impacts to traffic volumes in the Minneapolis area persisted for several months and have still not fully recovered at the time of writing.

Data from these disruptive events, as well as other events that occurred during the baseline time period, are included in the baseline data set. These events represent variability in traffic volumes and provide variability in the data. Without past disruptive events like the ones highlighted previously, the apparent impact of the COVID-19 pandemic would be more significant. By including these disruptive events, the analysis incorporates the fact that, occasionally, disruptive events occur.

Disruption in Weekly Traffic Cycles

Finally, it is considered how the weekly traffic variation shifted as a result of the COVID-19 pandemic. For this analysis, daily traffic volumes are considered and the percent change in traffic volume by day-of-week are compared with the prepandemic baseline data. Thus, it can be seen how substantially traffic volumes have changed on a day-by-day basis, i.e., traffic volumes on a particular Tuesday during the COVID-19 pandemic are compared with the expected prepandemic baseline expected traffic volumes for a Tuesday. The resulting percent change in traffic volume is plotted in Fig. 10. As can be seen in the daily traffic volumes, traffic volumes are roughly unchanged from the baseline data until roughly March 7, with the exception of large dips in traffic volumes on January 18 and February 14 that correspond to snow and low-temperature events, respectively, in the Minneapolis area. From roughly March 15 onward, one can see a drastic decrease in traffic volume, as discussed previously.

During the recovery period beginning roughly the second week of April, one can observe a strong cyclic variation each week, meaning that large deviations from the typical weekly traffic patterns appear. Because these data have been normalized by the day of week, this pattern indicates that traffic volume distribution within the week also changed, i.e., trips are distributed differently throughput the week than prior to the pandemic. This is likely the result of increased telecommuting, with many people staying at home during the week. Thus, although the COVID-19 pandemic and corresponding government orders significantly impacted traffic volume, they also impacted travel patterns in terms of types of trips being conducted as people stopped commuting to a regular work

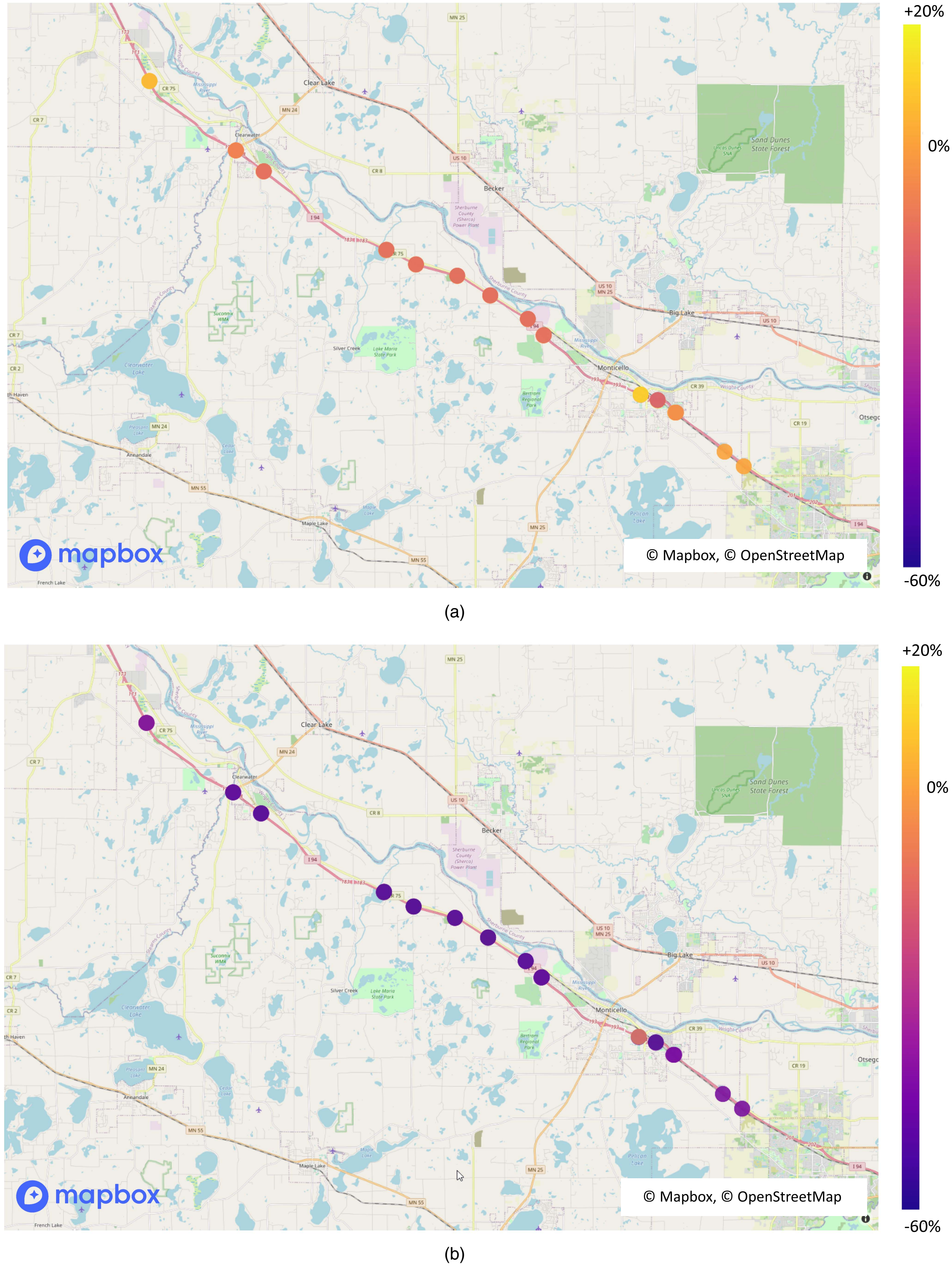
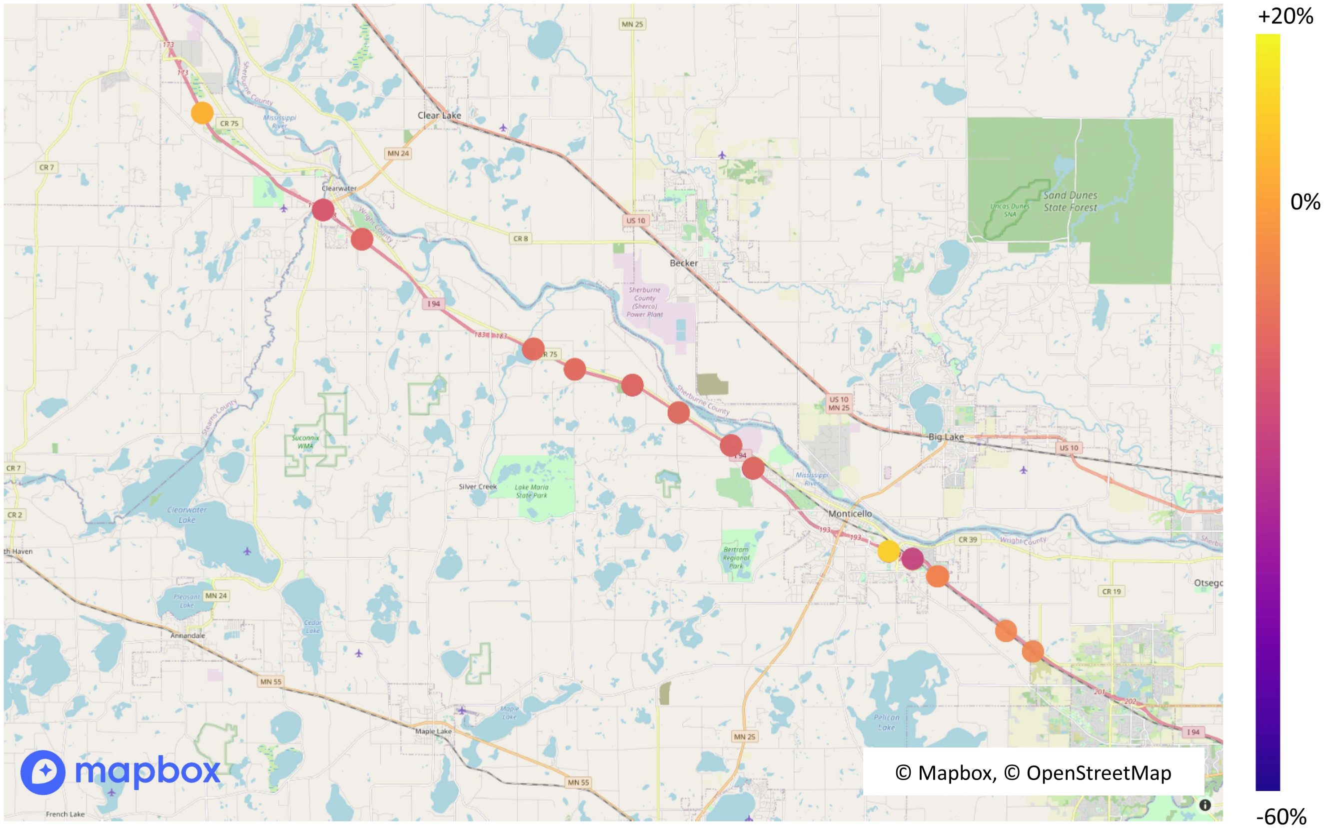
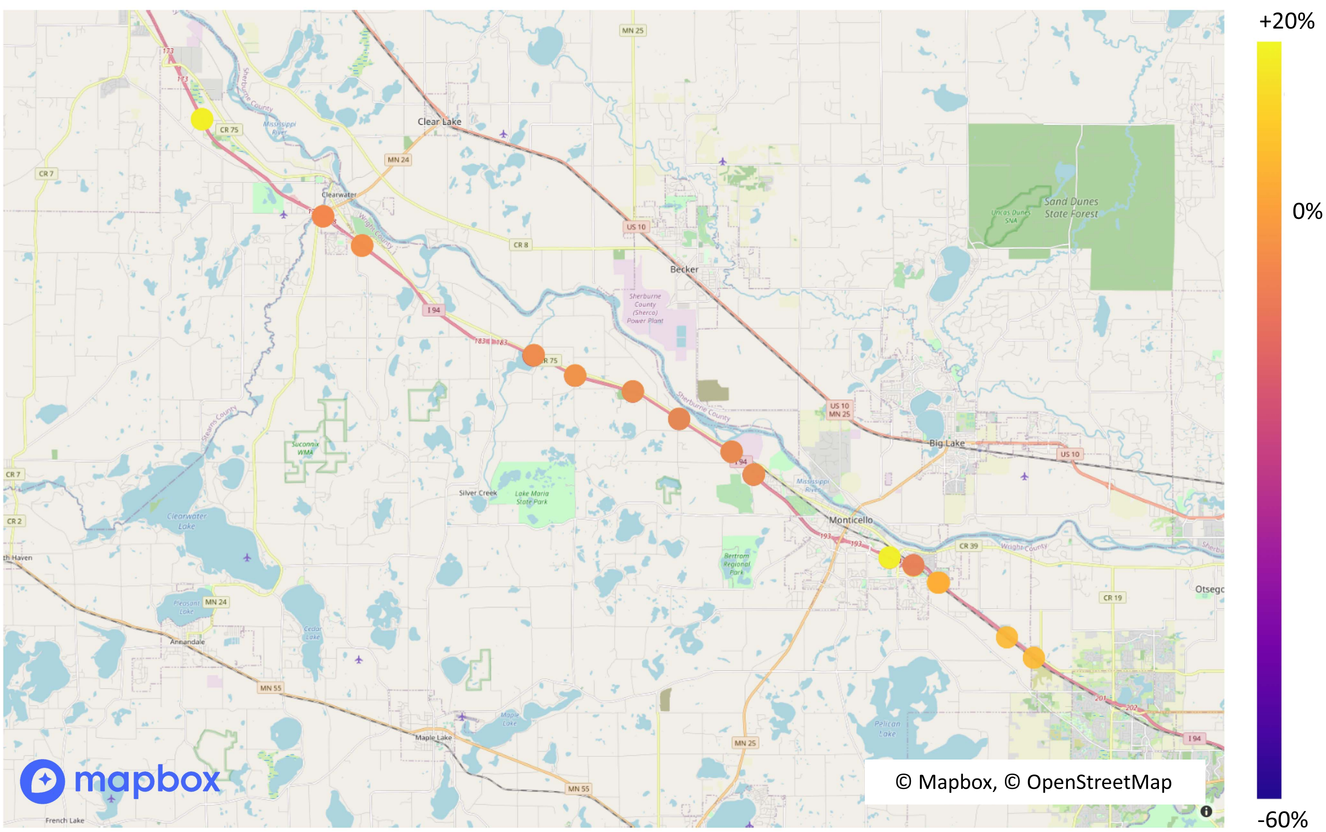


Fig. 7. Volume percent change by location at different dates along I-94: (a) March 1, 2020; (b) March 22, 2020; (c) June 7, 2020; and (d) July 12, 2020. (Map data from Mapbox and OpenStreetMap and their data sources. To learn more, visit https://www.mapbox.com/about/maps/ and http://www.openstreetmap.org/copyright.)



(c)



(d)

Fig. 7. (*Continued.*)

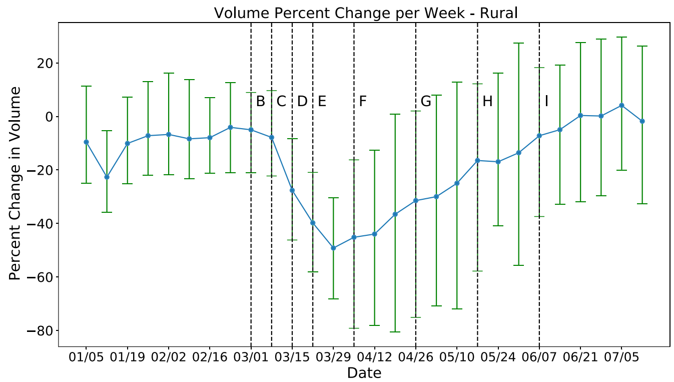


Fig. 8. Percent change in traffic volume along I-94 over time, averaged for all detectors. The bars represent one standard deviation in reductions across sensors in the study area.

place and instead gained the freedom to conduct many activities such as shopping on a more flexible schedule. This is also demonstrated in Table 3, where the mean change in traffic volume by day of week is presented for before the COVID-19 pandemic, during the shutdown, and during the subsequent recovery.

Table 3 indicates that after March 15, traffic was substantially reduced across all days. However, this reduction on a per-day basis was greater on weekend days than during the week. This is also true for Thursday and Friday, which follow the weekend trend and saw significant reductions in travel volume. This is also seen in Fig. 10, which shows both the overall trend as well as the weekly cyclic traffic volume. The day-to-day variability in weekly traffic volumes indicate that although many professionals worked from home for most of the week (e.g., a roughly 20% reduction in travel on Monday, Tuesday, and Wednesday), many of the employees who were still going in to the office on some days would work from home Thursday and Friday. The data also seem to suggest that

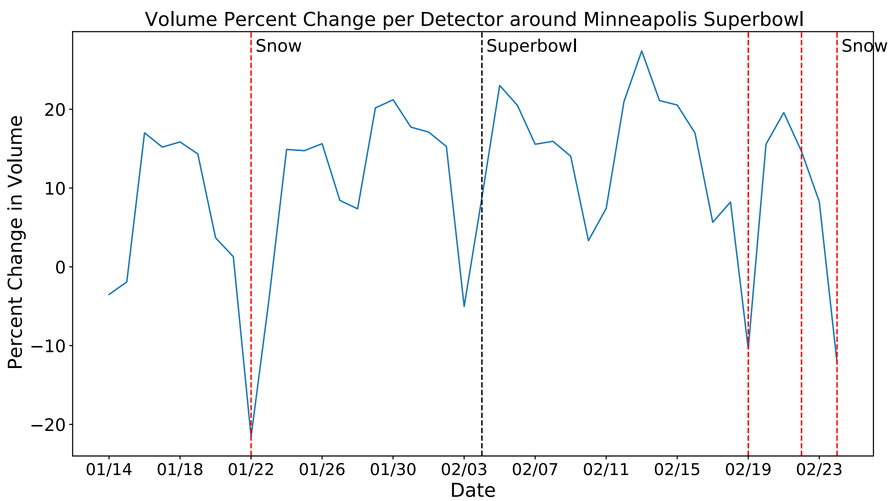


Fig. 9. Traffic volume percent change from baseline data during the 2018 Superbowl in Minneapolis. Snow events and the Superbowl are marked with dashes.

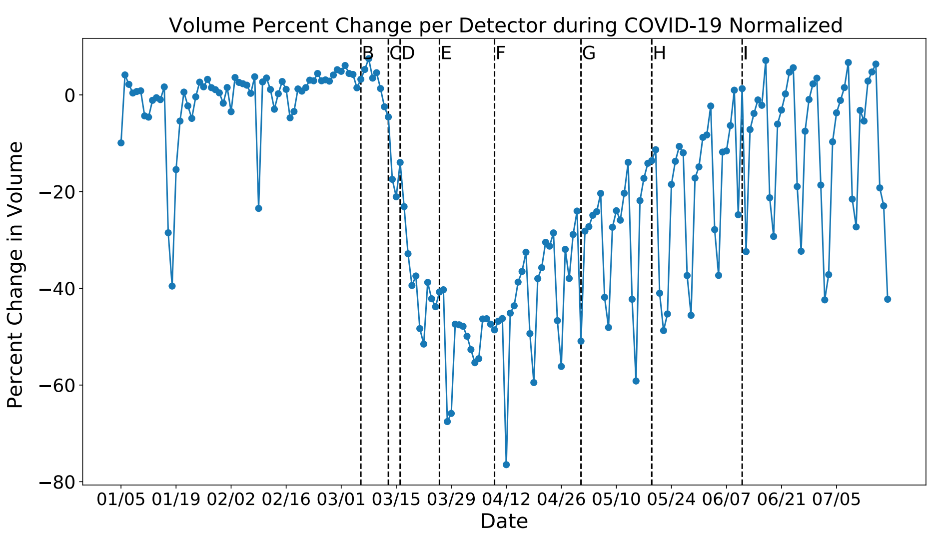


Fig. 10. Traffic volume percent change in Minneapolis during the first 28 weeks of 2020.

Table 3. Percent change in traffic volume from baseline data, averaged across all sensors in study area, by day of week

Time period	Sunday (%)	Monday (%)	Tuesday (%)	Wednesday (%)	Thursday (%)	Friday (%)	Saturday (%)
All data	−19.7	−11.9	−11.4	−11.4	−20.8	−26.2	−20.6
Pre-March 15	−3.8	1.6	1.8	1.2	0.0	−2.5	−3.7
Post-March 15	−28.6	−19.5	−18.8	−19.3	−32.3	−39.4	−30.0

Note: Prior to March 15, 2020, relatively little change is seen. During the COVID-19 pandemic, Thursday and Friday see the largest decreases in traffic volumes.

weekend activities were greatly reduced because people seemingly did not attend gatherings on weekends, which resulted in a roughly 30% reduction in vehicle volume.

Conclusions

In conclusion, the analysis presented in this study considers different measures of traffic volume impacts and abnormalities and applies them to the case study of traffic volumes in Minneapolis before, during, and after the COVID-19-related stay-at-home order in Minnesota. Percent change from a baseline data set, as well as a normalized change (i.e., *z*-score), are used to quantify abnormalities of individual sensors. However, due to the type of data collected, only trends in the overall traffic volume can be identified, and how traffic volumes in different vehicle classes (e.g., passenger vehicles versus trucks) evolved over the course of the COVID-19 pandemic could not be determined.

The analysis shows that the COVID-19 pandemic and associated stay-at-home order had a significant impact on traffic volumes. Specifically, in urban areas, traffic decreased by up to 50% from baseline expected traffic volumes at the start of the stay-at-home order. One interesting finding is that the recovery in terms of traffic volume during the first set of state-level restrictions in the spring and summer of 2020 was somewhat independent from the repeal of government orders restricting movement in Minnesota. Specifically, the individual levels of restriction being repealed did not directly lead to higher traffic volumes. Instead, traffic volumes continuously increased from the lowest point in March 2020. This suggests that although government restrictions played a significant role in reducing traffic at the start of the pandemic, other factors were more significant in determining people's travel patterns after the first wave of restrictions expired.

Adding to the evidence that the government orders themselves were not the most significant factor in influencing traffic volumes, traffic volumes had already reduced significantly before the stay-at-home order was issued in Minnesota, and they began rebounding when the stay-at-home order was first extended. By the time the stay-at-home order fully expired, traffic volumes had regained roughly half of the reduction seen due to COVID-19. Thus, although significant in dictating travel patterns, the stay-at-home order was not the significant driving factor influencing traffic volumes. Instead, the initial uncertainty when the first cases of COVID-19 were announced in Minnesota seems to have influenced traffic volumes more significantly and, over time, people began traveling again regardless of whether or not they were under a stay-at-home order.

When comparing the disruption to traffic of the COVID-19 pandemic with the disruptive event when Minneapolis hosted the Superbowl in February 2018, it was found that from the perspective of traffic volume reduction, the COVID-19 pandemic has been roughly five times as disruptive as the Superbowl, every day. Furthermore, although the duration of the Superbowl disruption was short, the disruption of the COVID-19 pandemic has been longstanding.

Another finding is that although traffic reduced for all days of the week, traffic was particularly impacted on Thursday, Friday, Saturday, and Sunday. This is likely a result of people reducing their leisure activities. The reductions in traffic volume on Thursdays and Fridays are likely the result of some professionals commuting for part of the week (Monday–Wednesday) and working remotely for the rest of the week (Thursday and Friday) in an effort to reduce contact.

Based on the findings on this research, although stay-at-home orders clearly reduced travel and corresponding traffic volumes, other factors such as fear of the pandemic may have been more significant driving factors in dictating traffic volumes. Thus, although the stay-at-home order and fear of COVID-19 were able to reduce travel and likely reduced the spread of the virus in Minnesota, this effect was temporary because people started to increase travel activity before the stay-at-home order was repealed.

Providing this understanding of how significant traffic volumes were disrupted as a result of the COVID-19 pandemic and associated stay-at-home order will help in understanding the impact of similar measures in the future to combat the spread of COVID-19 in future outbreaks or other pandemics. The analysis presented in this study provides a first view at the data to help understand how significant the disruption to mobility was as a result of COVID-19.

Data Availability Statement

Some or all data, models, or code that support the findings of this study are available from the corresponding author upon reasonable request.

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