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Substantial decreases in NO_2 concentrations measured by ground-based monitors in US cities during COVID-19 shutdowns from reduced transportation volumes

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Abstract

The air pollutant NO_2 is derived largely from transportation sources and is known to cause respiratory disease. A substantial reduction in transport and industrial processes around the globe stemming from the novel SARS-CoV-2 coronavirus and subsequent pandemic resulted in sharp declines in emissions, including for NO_2. Additionally, the COVID-19 disease that results from the coronavirus may present in its most severe form in those who have been exposed to high levels of air pollution and thus have various co-morbidities (Fattorini & Regoli, 2020). To explore these links, we compared averaged ground-based NO_2 sensor data from 11 US cities from a two-month window (March-April) over the previous five years versus the same window during shutdown in 2020. Levels of NO_2 declined roughly 12-41% in the 11 cities. This decreased coincided with a sharp drop in vehicular traffic from shutdown-related travel restrictions. To explore this link more closely, we gathered more detailed traffic count data in one city, Indianapolis, Indiana, and found a strong correlation between traffic counts/classification and vehicle miles travelled, and a moderate correlation between NO_2 and traffic related data. This

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finding indicates that we can use such analysis in targeting reduction in pollutants like NO_2 by examining and manipulating traffic patterns, thus potentially leading to more population-level health resilience in the future. Substantial improvements in air pollution and health outcomes may be targeted with local and state policy directives based on such analysis, thus perhaps leading to more population-level health resilience in the face of future pandemics.

Key Points:

- The shut-down policies related to COVID-19 pandemic resulted in a 12-41% decrease in ground-level NO_2 in 11 major U.S. cities studied

- Most of the NO_2 decline can be attributed to a drop in vehicular traffic, although industrial emissions confound this in some cases

- Ground-based sensor networks need to be expanded to capture local variation and to couple data more closely with population centers

Plain Language Summary:

The global shutdown to stem the explosive growth of the SAR-CoV-2 pandemic led to substantially improved air quality worldwide as many transport and industrial practices ground to a halt. The 2020 March and April values of one vehicular-related air pollutant, NO_2, decreased substantially in all the 11 U.S. cities analyzed here compared to a five-year average before 2020, using ground-based measurements of NO_2. The decrease ranged between 12% and 41%, with the

five Texas cities analyzed decreasing the least, potentially due to less restrictive lock-down procedures in that state and or the presence of other industry. Vehicle Miles Travelled (VMT) in the 11 cities decreased from 11%-51% in March (compared to January) and 62%-89% in April. Using vehicle count and classification sensors in Indianapolis, we find that there was a good match between NO_2 sensor values and the actual number of vehicles on the road, indicating that in some cases this might be a better metric than VMT at estimated emission concentrations. A more robust network of ground-based sensors that are matched to population density and the potential regions of highest emissions are needed to bridge the gap between regulatory compliance and protecting human health.

1. Introduction

Due to a 13-fold increase in Coronavirus disease 2019 (COVID-19) cases outside of China on March 11, 2020 the World Health Organizations Director General characterized it as a pandemic (*WHO Director-General's Opening Remarks at the Media Briefing on COVID-19 - 11 March 2020*). At the time of this writing, November 12, 2020, the Centers for Disease Control is reporting that there are over 10M cases of COVID-19 in the U.S. with the total deaths exceeding 239K (*CDC COVID Data Tracker*, 2020). This pandemic has resulted in instituting stay-at-home orders around the world, which has many negative externalities associated with it, but one positive one has been a marked decrease in many criteria air pollutants due to decreases in transportation volumes and industrial production (Nakada & Urban, 2020; Sharma et al., 2020), including reduced concentrations of nitrogen dioxide (NO_2). This change has also been quantified via satellite imagery which indicates a substantial drop in NO_2 tropospheric column of over 20%, from January to April 2020 versus the same time frame in 2019, over parts of China, Western Europe and United States (Bauwens et al., 2020), and similarly in 20 North American cities, Goldberg et al. (2020) calculated decreases in NO_2 during this similar timeframe, when adjusted for seasonality and meteorology in a North American city study, of between 9% and 43%.

As anthropogenic activities of nitrogen oxide (NOx) far surpass natural emissions (Walters et al., 2015) they have resulted in a three-to six-fold increase in nitrogen oxide ($NOx = NO + NO_2$) emissions since the pre-industrial era (Jaeglé et al., 2005). Sources of NOx include fossil fuel/biofuel combustion, industry, and transport category constituting of vehicles, ships, and aircraft, while as natural sources of NOx include soil nitrification-denitrification processes, wild fires and lightning (Walters et al., 2015). NO_2 from traffic emissions have shown to have profound and measurable health implications such as heart disease or upper respiratory infections in populations with increase in nonaccidental mortality (Cesaroni Giulia et al., 2013; Peel et al., 2005). Besides increasing acidification, exacerbating global climate change, decreasing visibility, and increasing ozone and aerosol in the troposphere (Bermejo-Orduna et al., 2014), NOx also induces small particle formation, and has shown to be positively correlated to adverse health conditions as a result of long-term exposure (Galloway et al., 2003; Marco et al., 2002).

The onset of COVID-19 has posed a unique opportunity to quantify changes in vehicular NO_2 emission as a result of reduction of vehicle volume in the U.S. To examine changes in NO_2 in cities and how that relates to vehicular traffic during the COVID-19 lock-down, we examine the

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impact of stay-at-home orders in March through April 2020 versus a five-year average of calibrated high-quality data from March-April from 2015-2019. We utilize 2020 daily raw data for NO_2, from EPA grade sensors in 11 large cities around the US. NO_2 concentrations are assessed and compared to traffic volumes by utilizing county vehicle miles travelled (VMT) data as a proxy, after adjusting for population density of the study regions. Additionally, we examined how Indianapolis's major traffic density metric, VMT compares to actual vehicles on the road and NO_2 concentrations, which may be a better metric of vehicular emissions in cities.

2. Methodology

2.1 NO_2 and Vehicle Miles Travelled (VMT) data

To examine the impact of stay-at-home orders, NO_2 daily averaged data from continuous ground level sensors from 11 major cities in the U.S. was downloaded from the respective state agencies for our study period. These cities were chosen for their population size and the availability of comparable data for air quality. We were unable to gather information on each individual sensor, however, based on Federal Audits required by the Environmental Protection Agency (EPA), generally a difference of < 15 percent difference is an acceptable federal standard that the states have to adhere to (*Air Sensor Guidebook*, 2014).

Data for NO_2 over the months of March and April 2020, were used as lock-down reference months, acknowledging that some states were phasing in lockdowns during March, and that states and cities often had different shut-down policies. This was compared to January 2020 data from those same sensors to determine in-year changes. The 2020 data is also compared to the mean 5-year sensor data (2015-2019) for March and April, in order to take the meteorological

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conditions into account. We identified two fixed monitors within each region (Cakmak et al., 2016), however, due to excessive number of missing days of data for San Antonio and Austin we utilized data from one sensor each in those locations. Additionally, for Queens we were able to identify only one fixed continuous monitor maintained by the state. For the remaining 8 cities we averaged NO_2 data over two fixed sensors each for 2020 and 2015-2019.

To obtain a uniform scale of vehicle usage, aggregate VMT data, generated at the county level, was accessed from StreetLight Data to examine changes in traffic patterns and emissions (Jia et al., 2020). Streetlight runs over 100 billion location data points gathered from smart phones and navigational devices connected to vehicles (cars and trucks), into an algorithm to aggregate and normalize travel patterns by region. Their metrics are validated not only against public sources or external sources, but also using private data in all states except Hawaii and Alaska (*StreetLight Volume Methodology & Validation White Paper*, 2019). Population percentage of the study area in the county it resided in was used to normalize the VMT data for this analysis, and from this point forward normalized VMT is presented and referenced in this document.

2.2 Indianapolis Traffic Sensor Data

Traffic counts are used in numerous studies to connect urban pollution like NO_2 to examine regions, their health impacts and the socio-economic disparities that occur as a result of it (Cakmak et al., 2016; Madariaga et al., 2003; Nicolai et al., 2003). For this study, we downloaded daily traffic volume and classification data of vehicles from 5 continuous sensors placed on major roadways in Indianapolis, identification numbers 990362, 950109, 990309, 990311, and 991392, reported by the Indianapolis Department of Transportation (INDOT). This data is publicly available via INDOT's online Traffic Count Database System (TCDS). March and April 2020 daily counts were examined against the count and classification data from January 2020 for the referenced continuous sensors. INDOT has 15 vehicle classifications, however, we focused on total vehicular traffic, total cars, and classification of motorcycle, car, pickup, and bus as a sub-category (1-4). Classification 5 and above were primarily trucks with varying axles (*Traffic Count Database System (TCDS)*, 2020)

3. Results

3.1 NO_2

A reduction between 12%-41% in the 2020 NO_2 March-April averages is observed in all locations when compared to the 5-year averages from that respective time frame (Table 1, Table S1). The percentage drop in NO_2 values when 2020 values are compared to the 5-year averages between January and March range from 11%-56% and 4%-43% respectively (Table 1, Table 1S). While as January and April reflect a NO_2 drop ranging from 14%-65% in 2020 and a drop of 13%-51% in the 5-year averages (Table 1, Table S1). Between January and March, San Antonio was the only location where the 2020 percent change was lower than the 5-year average percent change (Figure 1). From January to April (Figure 1), the percent changes in 2020 and the 5-year averages of San Antonio and Austin were almost the same while the other 9 locations showed a sharp reduction in NO_2 values in 2020, compared to the same 2-month window from 2015-2019 (Figure 1). Excluding the cities of Austin and San Antonio from January to April in 2020, Indianapolis had the smallest reduction of NO_2 at 33% and San Francisco had the largest reduction of NO_2 values at 65% (Table 1).

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Seasonal changes in NO_2 naturally occur and must be considered. In summer, NOx and other volatile organic compounds from traffic and other sources result in photochemical smog, with December through February having seasonal maximum in the U.S. (A et al., 2008). Oxidation by photochemically produced OH in the summer reduces NOx, while lower concentrations of OH in the winter months results in an increased lifetime of NOx (Shah et al., 2020). Extrapolating further from Table 1, we see this in our multi-city data, with decreases in 2020 NO_2 values in March and April ranging from -37.66% to -48.13% compared to their respective average January values. In April 2020, Austin had the smallest reduction of -13.51% with San Francisco having the largest reduction of -64.93% (Table 1). These decreases constitute seasonal changes plus any change related to COVID lock-down policies in the various cities.

Location (NO_2 Sensors)	Jan (ppb)	Mar (ppb)	Apr (ppb)	2020 Change (Jan to Mar)	2020 Change (Jan to Apr)
LA	21.40	9.44	8.33	-55.89%	-61.08%
Indianapolis	10.54	9.38	7.08	-11.03%	-32.90%
San Francisco	13.84	7.81	4.85	-43.59%	-64.93%
Ft. Worth	10.15	6.56	5.35	-35.39%	-47.32%
Houston	11.70	7.04	7.11	-39.79%	-39.25%
San Antonio	8.06	4.96	4.04	-38.39%	-49.82%
Austin	12.43	10.26	10.75	-17.42%	-13.51%
Dallas	11.38	6.82	6.07	-40.05%	-46.67%
San Jose	16.74	9.45	6.07	-43.55%	-63.76%
San Diego	14.99	7.83	6.80	-47.76%	-54.62%

Queens-NY	20.55	12.04	9.12	-41.39%	-55.61%

Table 1. 2020 NO_2 averages and percent changes in 2020

To determine the typical seasonal decrease in NO_2 values and thus remove this from the seasonal plus COVID-related signals, we calculated the five-year averages for each city, with the assumption that this window would normalize for particular weather-related variations year-on-year. We found that the typical seasonal decreases were significantly less than the COVID-impacted 2020 decreases (Figure 1). With an exception of Ft. Worth, San Antonio, and Dallas, rest of the cities had a greater than 20% drop in March-April averages in 2020 versus the 5-year averages (Figure 2). On average between January and March and January and April in 2020, NO_2 values decreased by 14% when compared to their respective 5-year averages from 2015-2019 (Table 1, Table S1), indicating the significant impact of lock-downs and agreeing with the more regional results obtained by satellite analysis (e.g., Goldberg et al., 2020). We can visualize such impacts from the free use of tropospheric NO_2 monthly mean averages, from GOME-2 sensor from www.temis.nl, over the U.S. from April 2019 when compared to April 2020 (Figure S1)(Boersma et al., 2004).

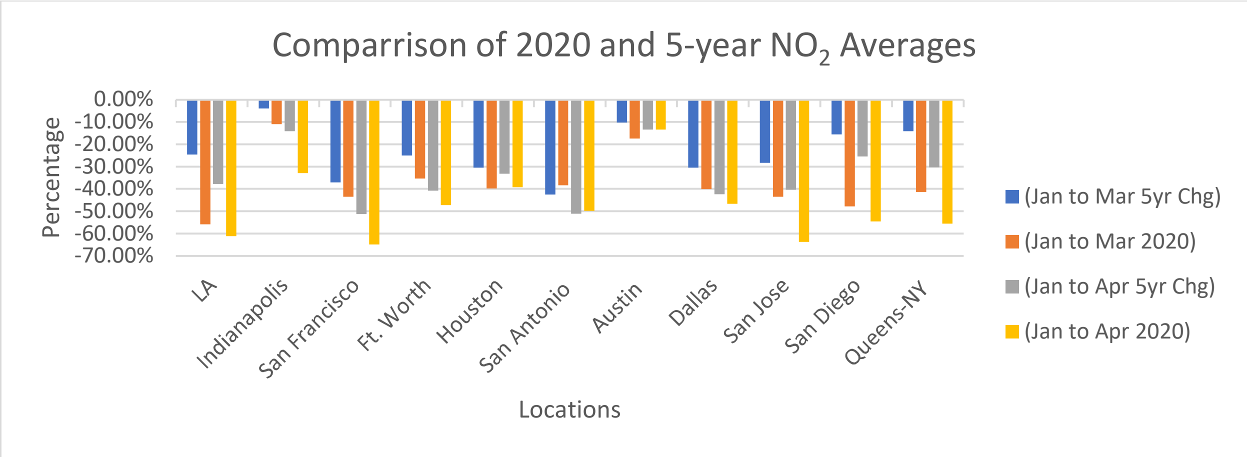

Figure 1. January to March and January to April NO_2 changes for 2020 and 5-year averages

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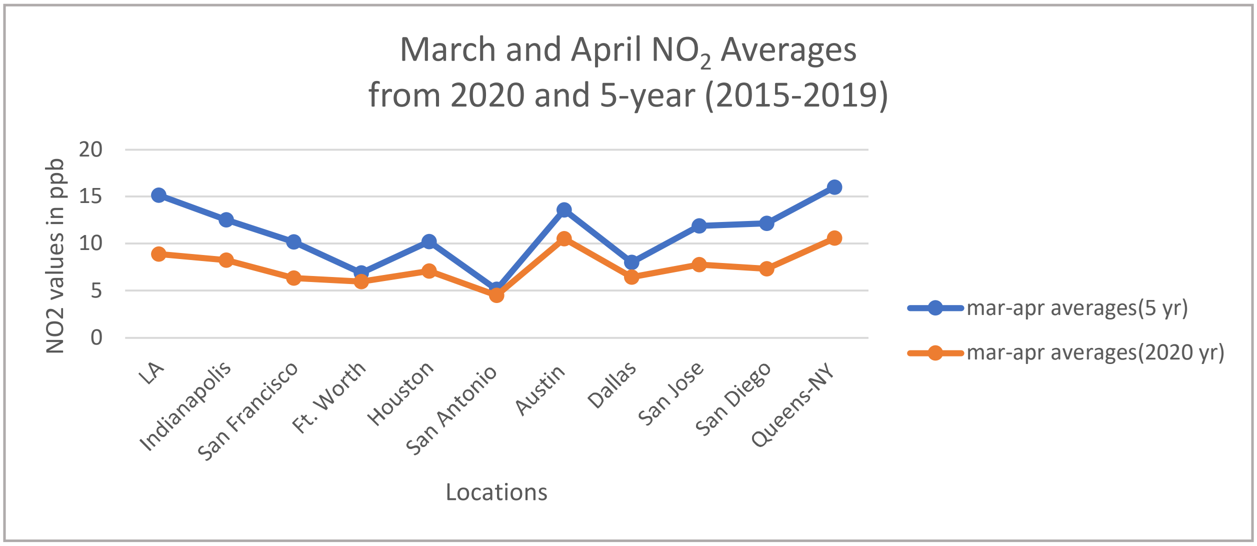

Figure 2. March and April combined NO_2 averages in parts per billion (ppb) from 2020 versus 5-year (2015-2019)

3.2 VMT and NO_2

Similar to the NO_2 trends between January, March and April in 2020 (Figure S2), VMT in all the locations significantly dropped with the implementation of stay-at-home orders (Fig 3). March showed a significant reduction in VMT between 11%-51% with NO_2 reduction being between 11%-56% (Table 3). April in comparison to January showed a much higher reduction of VMT between 62%-89% (Table 2) with NO_2 reduction being between 14%-65% (Table 3, Figure S3).

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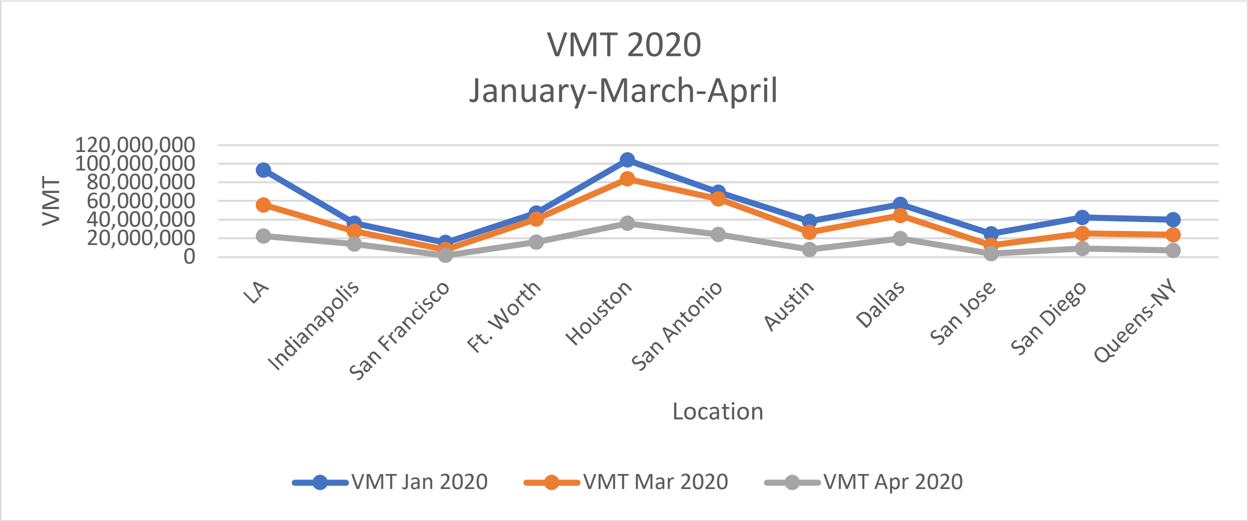

Figure 3. Vehicle Miles Travelled (VMT) for 11 cities from January, March, and April of 2020

Location	NO_2 Jan to Mar	VMT Jan to Mar	NO_2 Jan to Apr	VMT Jan to Apr
LA	-55.89%	-40.11%	-61.08%	-75.97%
Indianapolis	-11.03%	-23.95%	-32.90%	-61.87%
San Francisco	-43.59%	-49.12%	-64.93%	-89.07%
Ft. Worth	-35.39%	-13.57%	-47.32%	-66.50%
Houston	-39.79%	-19.38%	-39.25%	-65.29%
San Antonio	-38.39%	-10.73%	-49.82%	-65.29%
Austin	-17.42%	-30.97%	-13.51%	-78.88%
Dallas	-40.05%	-21.63%	-46.67%	-64.91%
San Jose	-43.55%	-50.62%	-63.76%	-86.35%

San Diego	-47.76%	-40.69%	-54.62%	-78.99%
Queens-NY	-41.39%	-40.29%	-55.61%	-82.66%

Table 3 NO_2 and VMT changes between January, March, and April 2020

Comparing the trends of NO_2 and VMT from January to March 2020, the percentage changes of NO_2 of Indianapolis, San Francisco, Austin and San Jose are higher than the VMT percent changes in the same time frame. For LA, Ft Worth, Houston, San Antonio, Dallas, and San Diego, VMT percent changes are lower than the NO_2 percent changes, with Queens being about the same (Figure S4). April, a month into the shutdown period in most states, NO_2 changes are consistently higher than the VMT percent changes in that time (Figure S5).

Spearman rank correlation statistics between NO_2 and VMT are presented in Table 4 below. San Diego, San Jose and Indianapolis have moderate significant correlation (r = 0.43-0.53) in the study with LA, Houston, San Francisco, and Queens having lower significant correlations (r = 0.29-0.39). High p-values for the four cities in Texas (Ft. Worth, San Antonio, Austin, and Dallas) indicate that in those locations we do not have strong evidence of a relationship between NO_2 and VMT variations. Examining the ratios of NO_2 to VMT for January to April 2020 for all 11 cities we find that on average a 1,000,000 reduction in VMT resulted in a reduction of 0.24 ppb in NO_2 for all cities. Austin was well below that average at 0.06 ppb and San Francisco had the highest impact of the decreased VMT with a reduction of 0.65 ppb) for an average of a 1,000,000 reduction in VMT (Table 5).

Location	X	Y	Correlation Coefficient	P-Value	P-Value < 0.05
LA	NO_2	VMT	0.3543	0.0051	X

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Indianapolis	NO_2	VMT	0.4569	0.0002	X
San Francisco	NO_2	VMT	0.3230	0.0111	X
Ft Worth	NO_2	VMT	0.1329	0.3072	
Houston	NO_2	VMT	0.2910	0.0229	X
San Antonio	NO_2	VMT	0.2225	0.0848	
Austin	NO_2	VMT	0.0454	0.7285	
Dallas	NO_2	VMT	0.1173	0.3679	
San Jose	NO_2	VMT	0.4295	0.0006	X
San Diego	NO_2	VMT	0.5320	0.0000	X
Queens	NO_2	VMT	0.3916	0.0028	X

Table 4. Spearman correlations between NO_2 and VMT in March and April of 2020

Location	**VMT Avg Chg (Jan-Apr) = [B]**	**NO_2 Avg Chg in ppb (Jan-Apr) = [A]**	**NO_2 /VMT = A/B (all cities)**
LA	-70,802,793.41	-13.07	$0.18*10^{-6}$
Indianapolis	-22,364,196.21	-3.47	$0.16*10^{-6}$
San Francisco	-13,824,506.67	-8.99	$0.65*10^{-6}$
Ft. Worth	-31,308,793.60	-4.80	$0.15*10^{-6}$
Houston	-67,843,483.92	-4.59	$0.07*10^{-6}$
San Antonio	-45,369,086.33	-4.01	$0.09*10^{-6}$
Austin	-30,210,481.83	-1.68	$0.06*10^{-6}$
Dallas	-36,617,918.66	-5.31	$0.15*10^{-6}$

San Jose	-21,531,553.94	-10.67	$0.50*10^{-6}$
San Diego	-33,359,270.66	-8.19	$0.25*10^{-6}$
Queens-NY	-33,089,110.33	-11.43	$0.35*10^{-6}$
Average			$0.24*10^{-6}$

Table 5. NO_2 and VMT ratios from January to April 2020 for cities and cities with significant correlations

3.4 Indianapolis VMT versus road sensor data

Given that the Spearman correlation between NO_2 and VMT in Indianapolis is significant, we examined the city further. An expanded Spearman correlation test indicates that the correlation between VMT, NO_2, and vehicle counts in March and April 2020 are all highly significant, with moderate correlations between VMT and $NO_2$and high correlations between total vehicles and VMT, as expected (Table 6).

Location	**X**	**Y**	**Correlation Coefficient**	**P-value**
Indianapolis	Avg Total Vehicles	VMT	0.90	<0.005
Indianapolis	Average Vehicles (class 1-4)	VMT	0.93	<0.005
Indianapolis	Avg Total Vehicles	NO_2	0.54	<0.005
Indianapolis	Average Vehicles (class 1-4)	NO_2	0.52	<0.005
Indianapolis	VMT	NO_2	0.46	<0.006

Table 6. Spearman correlation between vehicles and VMT and NO_2 in Indianapolis, March-April 2020

Average Counts of total vehicles, total cars, vehicle classification 1-4 (motorcycle, car, pickup, and bus), NO_2 and VMT show a decline in all categories in March and April when compared to January 2020 (Table 7). VMT percentage reduction in April versus January is almost two times

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that of the average total vehicles in Indianapolis and of the NO_2 percentage reduction in that time period (Table 8), indicating that a percentage reduction in the average total vehicles results in almost an equivalent percentage reduction in NO_2 in the city in that month. Extrapolating from Table 8 we can make the following 2 points regarding the change from January to April:

1. If a 50,000-unit reduction in average total vehicles, is equivalent to a 32% or a (Matthes et al., 2007) 0.07 ppb (0.32*3.47*50,000/764,515) average burden of NO_2
2. A 0.07 ppb average reduction in NO_2 is equivalent to a 451,150 (22,364,196*0.07/3.47) reduction in average VMT. It should be noted that over 97% of the average VMT reduction could be attributed to vehicle class 1-4 (745,556/764,515 *100)

Month	Avg Total Vehicles	Avg Total Cars	Avg Vehicles (1to4)	Avg NO_2 2020 (ppb)	Avg VMT 2020
Jan	336971	239289	298476	10.54	36147631
Mar	310327	210699	268216	9.38	27490875
Apr	220784	137125	184166	7.08	13783435

Table 7. Indianapolis vehicle count, NO_2, and VMT in 2020

Variable	January	April	Unit_Chg (Jan-April)	Pct_Chg (Jan-Apr)
Avg_VMT	36,147,631	13,783,435	-22,364,196	-61.87%
Ag_NO_2(ppb)[1]	10.54	7.08	-3.47	-32.90%
Avg_tot_veh[2]	2,089,221	1,324,706	-764,515	-36.59%
Avg_tot_cars[3]	1,483,595	822,751	-660,844	-44.54%

Avg_veh (1-4)[4]	1,850,556	1,105,000	-745,556	-40.29%

Table 8. Percentage and unit change of vehicles, VMT, and NO_2 from January to April to January 2020

[1] NO_2 averaged from two sensors in Indianapolis

[2] Total count of vehicles averaged over the 5 sensors in Indianapolis[3] Total count of cars averaged over the 5 sensors in Indianapolis

[4] Total count of vehicle class 1-4 (motorcycle, car, pickup, and bus) averaged over the 5 sensors in Indianapolis

4. Discussion

High vehicular emissions can result in corridors of heavy air pollution (Redling et al., 2013) in rural and urban regions. NO_2 pollution, a tracer for vehicular emissions, has been linked to adverse health effects for instance increased asthma events in predominantly urban areas (Achakulwisut et al., 2019). A 20 ppb increase in NO_2 has been found to increase chronic obstructive pulmonary disease (COPD) hospital visits, cardiovascular disease, lung cancer in adults, and respiratory mortality (Cesaroni Giulia et al., 2013; Peel et al., 2005). The onset of COVID-19, and the stay at home orders in March and April, presented an opportunity to examine the changes in NO_2 concentrations and their relationship to VMT in 11 cities in the U.S. with implications for local health outcomes.

Satellite data has been shown to be under reported in urban regions versus remote regions with daily NO_2 retrievals varying up to 40% (Lamsal et al., 2014). Our analysis of the impacts of stay at home orders utilized ground-based sensor data from 11 U.S. cities. We found an average reduction of NO_2 of 31% measured in March and April 2020 when compared with their 5-year averages (2015-2019) (Table 1, Table S1)). January to April 2020 resulted in a drop between

14%-65% versus its respective 5-year average drop between 13%-51%. Four Texas cities had a poor correlation between VMT and NO_2 (Ft. Worth, San Antonio, Austin, and Dallas). This consistent offset is likely due to differences in the air being sampled with each approach (i.e., ground-level versus troposphere scale).

The VMT reduction in April 2020 ranged between 62% and 89% (Table 3), when compared to January 2020 Average ratio of NO_2/VMT for the 11 locations indicates that for every 1,000,000 less VMT, NO_2 decreases by 0.24 ppb (Table 5). A 1,000,000 average VMT drop in San Francisco resulted in the most significant decrease in NO_2 (0.65 ppb) and Houston resulted in the least significant decrease (0.07 ppb). The petrochemical industry in Texas and particularly in the greater Houston area, probably plays a significant role in NO_2 production (Jobson et al., 2004), and thus the VMT-NO_2 relationship is not likely the only factor influencing the scale of observed decreases in NO_2.

The lack of observed significant correlations between NO_2 and VMT for the four Texas cities remains unresolved. We suggest two options: (1) the locations of the fixed AQ sensors locations in relation to emission sources as related to traffic and non-traffic need to be identified and incorporated with meteorology as their absence may not be ideal for capturing the more regional emission sources that are better characterized by satellite observations (e.g., Goldberg et al., 2020) that might be an issue for more sprawling cities, and/or (2) VMT along with specific traffic volume and classification analysis from platforms like StreetLight, may be a more robust metric for extrapolating the local impacts of NO_2 emissions from vehicle sources. A much denser array of high quality ground-based sensors would likely have to be in place to address option (1) above, but with option (2), we can, at least for one of the cities (Indianapolis), compare NO_2 to actual vehicle count data for several locations to address the issue.

We can use traffic counts in addition to VMT to create localized indices that can assist local governments to plan and/or to adjust traffic flows to address the impacts of high NO_2 values. In future studies, placement of NO_2 sensors in relation to the NO_2 sources, which would also impact the sensors readings, should be considered. This NO_2/VMT ratio (Table 5) should be tested in other cities in different seasons which could be then used as a proxy in examining NO_2 production in different regions while gauging the impact of transportation changes. This can assist in classifying the impact of traffic changes in regions from the most sensitive to the least. In addition to sensor placement, meteorological conditions like temperature, wind speed, relative humidity, and precipitation also play a role in transport of atmospheric gases (Tobías et al., 2020), which were also not considered in this analysis. Such conditions are not uniform spatially and have shown to cause column NO_2 readings to differ by about 15% over monthly timescales (Goldberg et al., 2020)—high winds in particular can play a role in dispersing NO_2 pollutant concentrations throughout the year (Czarnecka & Nidzgorska-Lencewicz, 2005).

A deeper look into vehicle count and classification in Indianapolis indicates that the drop in average total vehicles percentage is almost identical to the percentage drop in its NO_2 values (Table 8). A further breakdown of Table 8 enables us to quantify that impact of vehicle count and class changes on not only NO_2 but also the average VMT. A 50,000-unit reduction in average total vehicles in Indianapolis would be equivalent to a VMT reduction of 451,150, which in turn should yield a decrease in NO_2 values of 0.07 ppb. Building on this process in time and space, this calculation can be useful in examining regions that should be targeted first and would have the biggest impact of the reduction in NO_2 through traffic manipulation. In places like Houston where there is a presence of other significant industry, their emission impacts should also be incorporated for a more comprehensive understanding.

In qualitative terms, the observed substantial reductions in NO_2 would, all other things being equal, provide some benefits to human health. With the return to “business-as-usual” practices, these health benefits will be transitory. Satellite measurements of NO_2 are outstanding for capturing regional trends, but the heterogeneity of NO_2 at the ground level in a given city (e.g., Coppalle et al., 2001) is not well-captured, and thus pinpointing emission sources that are proximal to population centers at the fine scale should be a high priority for city planners and transportation design. This latter point is critical in that the highest concentrations of NO_2 and many other criteria air pollutants are disproportionately located in lower income communities (Miranda et al., 2011; Cakmak et al., 2016). The overlapping issues of poor air quality and particular susceptibility of these same communities to severe COVID disease speaks to the need to better constrain ground-level air pollution levels with an eye toward applying health equity solutions in cities.

5. Conclusions

The pandemic-driven shutdown policies instituted in cities across the U.S. substantially decreased many harmful air pollutants, including NO_2 (e.g., Berman and Ebisu, 2020; Goldberg et al., 2020). We find this stable reduction within cities using ground-based monitors, and it is largely tied to reduced traffic volume, with other factors, such as industrial emissions, playing a variable role. Although ground-based monitoring ties the concentration data much more closely to communities and local health impacts than does more regionally comprehensive satellite data, the paucity of monitors and likely disconnects between metrics that are meant to capture traffic volume reduces their effectiveness from a public health standpoint.

This observed reduction in urban NO_2 concentrations, a rare silver lining of the devastating pandemic, is likely temporary, but it does point to the tight connection between traffic-related pollution sources and local impacts. This connection prompts the two-fold issue that local air pollution hotspots exacerbate diseases like COVID and are currently under-studied. Two actions that city planners can take to promote health equity in their communities are to implement environmental monitoring programs that link data points (i.e., monitors) more strategically to population density, and to implement local transportation and zoning policies that protect community health and build health equity into the system.

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aspect of this project, can be accessed at the Streetlight data hub (https://www.streetlightdata.com). The vehicle count data for the city of Indianapolis can be accessed at the Indiana Department of Transportation site (www.indot.in.gov).

Conflicts of Interest:

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

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