Substantial decreases in NO2 emissions from reduced transportation volumes in US cities during COVID-19 shutdowns reveal health vulnerabilities of urban populations

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Abstract

The air pollutant NO is derived largely from transportation sources, and is known to cause various respiratory diseases. 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. 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. To explore these links, we compared ground-based NOsensor data from 15 US cities from a one month window in 2019 versus the same window during shutdown in 2020. Levels of NO declined roughly 20-60% in 13 of the 15 cities in 2020, linked to similar declines in traffic volume in those cities. To broaden the spatial analysis beyond the individual ground-based monitors, satellite data for tropospheric NO was also analyzed, and was largely consistent with the ground measurements. Many of the cities studied had a substantial percentage of the population with various pre-existing conditions, and a relationship was found between NO levels, respiratory disease, and COVID-19 case counts. This finding indicates that substantial improvements in air pollution and health outcomes can be achieved quickly with local and state policy directives, perhaps leading to more population-level health resilience in the face of future pandemics.

Supporting Information

Substantial decreases in NO_2 emissions from reduced transportation volumes in US cities during COVID-19 shutdowns reveal health vulnerabilities of urban populations

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	VMT_normalized area	**Pct_ped asthma**	**Pct_adult asthma**	**Pct_adult asthma**	**Pct copd**
VMT_normalized_area	1				

	VMT_-normalized area	Pct_ped asthma	Pct_adult asthma	Pct_adult asthma	Pct copd
pct_ped asthma	-0.335513897	1	1		
pct_adult asthma	0.424744751	-0.209894652	-0.209894652	1	
pct_copd	-0.051055607	0.616866122	0.616866122	0.3427601	1
pct-lung cancer	0.192682223	0.665499529	0.665499529	0.330156319	0.844530689

Table S1. Disease Correlation

County	*City*	*City*	**Pct adult asthma**	**Pct adult asthma**	**Pct ped asthma**
Queens	Queens	NY	NY	8.17%	1.24%
Philadelphia	Philadelphia	Philadelphia	Philadelphia	7.90%	2.11%
Maricopa	Maricopa	Phoenix	Phoenix	7.71%	1.92%
Marion	Marion	Indianapolis	Indianapolis	7.44%	2.14%
San Francisco	San Francisco	San Francisco	San Francisco	7.33%	0.83%
Mecklenburg	Mecklenburg	Charlotte	Charlotte	7.27%	2.71%
Duval	Duval	Jacksonville	Jacksonville	6.81%	1.68%
Los Angeles	Los Angeles	LA	LA	6.66%	1.34%
San Diego	San Diego	San Diego	San Diego	6.66%	1.33%
Santa Clara	Santa Clara	San Jose	San Jose	6.64%	1.35%
Travis	Travis	Austin	Austin	5.81%	1.72%
Bexar	Bexar	San Antonio	San Antonio	5.55%	2.02%
Tarrant	Tarrant	Fort Worth	Fort Worth	5.51%	2.08%
Dallas	Dallas	Dallas	Dallas	5.51%	2.07%
Harris	Harris	Houston	Houston	5.47%	2.11%

Table S2. Percent Asthma

Correlation	**Pct_adult asthma**
pct_adult asthma	1
death_rate_covid	0.467336406
cases_rate_covid	0.578234609
VMT_jan_normalized	0.424744751
pct_ped_asthma	-0.209894652
pct_copd	0.3427601
pct-lung cancer	0.330156319
mean_NO_2_2019	0.318820764
raster_mar2019	0.218847794
raster_apr2019	0.187058132

Table S3. Correlation of percent adult asthma

Correlations	**VMT_jan_normalized**
VMT_jan_normalized	1
cases_rate_covid	0.713780978
raster_mar2019	0.592131794
raster_apr2019	0.517037472
pct_adult asthma	0.424744751
death_rate_covid	0.328400892
pct-lung cancer	0.192682223
Mean_ NO_2_2019	0.031041247
pct_copd	-0.051055607
pct_ped asthma	-0.335513897

Table S4. Correlation of VMT normalized

Correlation	**Cases_rate_covid**
cases_rate_covid	1
raster_mar2019	0.825389115
death_rate_covid	0.78354049
VMT_jan_normalized	0.713780978
raster_apr2019	0.709177717
pct_adult asthma	0.578234609
pct-lung cancer	0.379933163
Mean_ NO_2_2019	0.229179331
pct_copd	0.113024761
pct_ped asthma	-0.220742254

Table S5. Correlation of COVID-19 cases rate

Correlation	Death_rate_covid
death_rate_covid	1
cases_rate_covid	0.78354049
raster_mar2019	0.69124339
raster_apr2019	0.518801979
pct_adult asthma	0.467336406
VMT_jan_normalized	0.328400892
pct-lungcancer	0.07930734
Mean_NO_2_2019	-0.073176656
pct_copd	-0.085953128
pct_pedasthma	-0.307275369

Table S6. Correlation of COVID-19 death rate

CountyName	**City**	**Cases_rate_covid**
Queens	NY	1.90%
Philadelphia	Philadelphia	0.66%
Marion	Indianapolis	0.47%

CountyName	**City**	**Cases_rate_covid**
Los Angeles	LA	0.18%
San Francisco	San Francisco	0.14%
Harris	Houston	0.12%
Travis	Austin	0.11%
Dallas	Dallas	0.10%
Mecklenburg	Charlotte	0.10%
Duval	Jacksonville	0.10%
San Diego	San Diego	0.08%
Tarrant	Fort Worth	0.08%
Santa Clara	San Jose	0.07%
Maricopa	Phoenix	0.07%
Bexar	San Antonio	0.06%

Table S7. COVID-19 cases in 15 cities

CountyName	**City**	**Death_rate_covid**
Queens	NY	10.42%
Santa Clara	San Jose	5.92%
Marion	Indianapolis	4.74%
Los Angeles	LA	4.66%
Maricopa	Phoenix	3.89%
San Diego	San Diego	3.88%
Bexar	San Antonio	3.76%
Mecklenburg	Charlotte	3.27%
Tarrant	Fort Worth	2.86%
Dallas	Dallas	2.64%
Philadelphia	Philadelphia	2.61%
Travis	Austin	2.44%
San Francisco	San Francisco	1.79%
Duval	Jacksonville	1.75%
Harris	Houston	1.53%

Table S8. COVID-19 death rate in 15 cities

correlations	**death_rate_covid**	**cases_rate_covid**
pct_adult asthma	0.467336406	0.578234609
pct_ped asthma	-0.307275369	-0.220742254
pct_copd	-0.085953128	0.113024761
pct-lungcancer	0.07930734	0.379933163

Table S9. Correlation of diseases and COVID-19 for all 15 cities studied.

Column1	**Mean_ NO_2_2019**
Mean_ NO_2_2019	1
raster_apr2019	0.356824066
pct_adult asthma	0.318820764

Column1	Mean_ NO_2_2019
raster_mar2019	0.27820681
cases_rate_covid	0.229179331
pct-lungcancer	0.065654954
VMT_jan_normalized	0.031041247
pct_copd	0.005648168
pct_ped asthma	-0.055242012
death_rate_covid	-0.073176656

Table S10. Correlation of NO_2 with disease in all 15 cities measured

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Abstract

The air pollutant NO_2 is derived largely from transportation sources, and is known to cause various respiratory diseases. 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. To explore these links, we compared ground-based NO_2 sensor data from 15 US cities from a one month window in 2019 versus the same window during shutdown in 2020. Levels of NO_2 declined roughly 20-60% in 13 of the 15 cities in 2020, linked to similar declines in traffic volume in those cities. To broaden the spatial analysis beyond the individual ground-based monitors, satellite data for tropospheric NO_2 was also analyzed, and was largely consistent with the ground measurements. Many of the cities studied had a substantial percentage of the population with various pre-existing conditions, and a relationship was found between NO_2 levels, respiratory disease, and COVID-19 case counts. This finding indicates that substantial improvements in air

pollution and health outcomes can be achieved quickly with local and state policy directives, 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 20-60% decrease in ground-level NO_2 in most U.S. cities
- Most of the NO_2 decline can be attributed to a sharp drop in vehicular traffic during the shut-down
- Pre-existing conditions that worsen COVID-19 disease correlated with NO_2 and COVID-19 incidence and mortality data

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. Air pollution influences morbidity and mortality, causing co-morbidities that seem to be linked to more severe cases of COVID-19. One vehicular-related air pollutant, NO_2, decreased substantially in concert with lowered traffic volume in nearly all of the 15 U.S. cities analyzed here using ground-based measurements of NO_2. Additionally, satellite-based measurements were consistent with the ground-based network, filling in key spatial data gaps and contextualizing the sparse ground-level data with more spatially integrative satellite observations. Health data from these cities show significant correlation between NO_2, several pre-existing conditions, and COVID-19 cases and deaths, supporting the concept that air pollution might "pre-condition" some urban populations. The silver lining provided by shut-down related air quality improvements are likely temporary, but lay bare the reality that air pollution likely makes inhabitants of some cities quite vulnerable to those very co-morbidities that exacerbate COVID-19 disease.

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 the Centers for Disease Control reported that there are 1.7M cases of COVID-19 in the U.S. with the total deaths exceeding 100K (https://www.cdc.gov/coronavirus/2019-ncov/cases-updates/cases-in-us.html). 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 emissions of nitrogen dioxide (NO_2). This change has also been quantified via satellite imagery which indicates more than 10% decline in tropospheric pollutant measurements over inhabited regions around the globe (Liu et al., in review; Venter et al., 2020).

As anthropogenic activities 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). Road emissions from tail pipe emissions, resuspended dust particles and friction processes result in NOx, carbon monoxides and volatile organic compounds (VOC's) which has profound and measurable health implications in populations (Cesaroni Giulia et al., 2013; Krzyżanowski et al., 2005; Peel et al., 2005). Besides increasing acidification, global climate changes, decrease in visibility, and ozone and aerosol increases in the troposphere (Bermejo-Orduna et al., 2014), NOx also increases small particle formation (Galloway et al., 2003).

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. Due to its adverse health impacts, NO_2 emission, a precursor to ground-level ozone and particulate matter concentration, has resulted in its usage as a marker for combustion emissions over regions (Bechle et al., 2011). To examine changes in NO_2 in cities and how that relates to vehicular traffic and health status of the population during the COVID-19 pandemic, we examine the impact of stay-at-home orders from March 23 – April 24, 2020, as compared with March 25 - April 26, 2019. We utilize calibrated high-quality daily data for NO_2 from EPA grade sensors in cities around the US. NO_2 emissions in 15 of the top 17 most populous cities in the U.S. (Table 1) are assessed, and compared to satellite results. We also examined traffic comparative traffic volumes, and assessed the health status of inhabitations of cities to project potential theoretical health benefits of NO_2 reductions and vulnerabilities to severe forms of COVID-19 disease due to asthma, COPD and lung cancer

2. Methodology

2.1 NO_2 and Vehicle Miles travelled (VMT) data

To examine the impact of the stay-at-home orders, NO_2 daily averaged data from continuous ground level sensors from road segments in 15 of the top 17 populated (Table 1) cities in the

U.S. were accessed through the respective state agencies for our study period. Due to the recent nature of this data, the 2020 NO_2 values had not been validated at the time of retrieval.

Population – U.S. Census Bureau			
City	County	State	Population Estimate (July 1,2019
Indianapolis	Marion	Indiana	876,384
San Francisco	San Francisco	California	881,549
Charlotte	Mecklenburg	North Carolina	885,708
Columbus	Franklin	Ohio	898,553
Fort Worth	Tarrant	Texas	909,585
Jacksonville	Duval	Florida	911,507
Austin	Travis	Texas	978,908
San Jose	Santa Clara	California	1,021,795
Dallas	Dallas	Texas	1,343,573
San Diego	San Diego	California	1,423,851
San Antonio	Bexar	Texas	1,547,253
Philadelphia	Philadelphia	Pennsylvania	1,584,064
Phoenix	Maricopa	Arizona	1,680,992
Houston	Harris	Texas	2,320,268
Chicago	Cook	Illinois	2,693,976
Los Angeles	Los Angeles	California	3,979,576
New York	Queens	New York	8,336,817

Table1. Population data from U.S. Census Bureau (U.S. Census Bureau, May2020)

Seven of the 15 cities traffic volume data was also accessed as reported by Department of Transportation’s continuous sensor on a roadway segment in the respective cities. To get a uniform scale of vehicle usage, aggregate VMT data for the 15 counties was accessed from StreetLight Data (https://www.streetlightdata.com/our-data/) which run over 100 billion location data into an algorithm to aggregate and normalize travel patterns by region.

2.2 Tropospheric NO_2 data

For monthly averaged NO_2 tropospheric data (January through April of 2020), we acknowledge the free use of tropospheric NO_2 column data from the Global Ozone Monitoring Experiment-2 (GOME-2 (METOP-B)) satellite from www.temis.nl. This sun-synchronous satellite processes NO_2 concentrations from the ground up to about 10 Km and has a geometric pixel resolution of 60 x 30 km^2. Due to environmental uncertainties and the density of the slant column retrieved by the sensor this data can accurately estimate tropospheric column with 35-60% precision (Boersma et al., 2004). Major chemical and transport processes related to NO_2, along with cloud cover, also play a role in the retrieval process and uncertainty in these values. However, the integrated tropospheric column of NO_2 data is dominated by lower tropospheric amounts of NO_2 (Ma et al., 2006), which makes it a useful variable to incorporate for such studies. Fifteen locations of the continuous NO_2 sensors were used to extract pixel values of the tropospheric NO_2 data utilizing ESRI's ArcGIS Desktop 10.8, which was then rescaled on a scale of 0-100 for visual comparison.

2.3 Health Data

To assess the health status of the cities studied, Estimated Prevalence and Incidence of Lung Disease data from American Lung Association (ALA) was accessed. This data estimation is available at a county level and is based on a Behavioral Risk Factor Surveillance Survey conducted in 2017 and 2018 Centers for Disease Control's (CDC) joint report with other state and national registries (https://www.lung.org/research/trends-in-lung-disease/prevalence-incidence-lung-disease). Additionally, county-level COVID-19 cases and death data was accessed from USAFacts (https://usafacts.org/), a not-for-profit organization providing U.S. government data.

3. Results

A sharp reduction in NO_2 was observed in 13 of the 15 cities examined, based on the same ~1-month window from 2019 to shut-down conditions in 2020 (Table 2). All cities except Jacksonville, Florida showed a decline in the continuous NO_2 sensors, from -4% to -63%, with an average across the cities of -26% for weekdays and -24% on weekends (Table 2). Averaged monthly values during the study period show a decline in NO_2 values ranging from -5.89% to -59.7% (Table 3).

NO2 by City	Mean wkday 2019 (ppb)	Mean wkday 2020 (ppb)	Mean wkend 2019 (ppb)	Mean Wkend 2020 (ppb)	NO2 pct_chg wkday	NO2 pct_chg wkend
Jacksonville	17.77	19.16	11.05	15.29	7.87%	38.35%
Fort Worth	8.04	7.70	7.00	6.10	-4.24%	-12.86%
Houston	19.71	17.63	13.31	9.74	-10.53%	-26.85%
Austin	14.38	11.59	7.93	7.49	-19.41%	-5.52%
Indianapolis	8.99	7.13	7.09	5.84	-20.69%	-17.64%
Phoenix	17.05	13.45	12.88	8.61	-21.12%	-33.15%
Charlotte	5.60	4.32	3.05	3.38	-22.81%	10.74%
Dallas	4.63	3.42	2.78	2.13	-26.19%	-23.42%
San Francisco	8.16	5.80	5.38	2.75	-28.92%	-48.84%
NY	13.16	9.00	13.63	9.85	-31.60%	-27.77%
San Antonio	9.31	6.26	7.31	6.31	-32.75%	-13.68%
LA	16.40	10.75	13.75	6.13	-34.45%	-55.45%
San Diego	15.09	9.71	11.63	4.88	-35.65%	-58.06%
San Jose	9.58	5.46	6.25	3.50	-43.04%	-44.00%
Philadelphia	29.51	10.87	22.93	12.45	-63.18%	-45.68%

Table 2. NO_2 mean values in parts per billion

City	Mean_NO_2 2019	Mean_NO_2 2020	Pct change
Jacksonville	16.03	18.22	13.67%
Fort Worth	7.77	7.31	-5.89%
Houston	18.16	15.72	-13.43%
Austin	12.82	10.60	-17.33%
Charlotte	4.96	4.09	-17.51%
Indianapolis	8.53	6.82	-20.07%
Phoenix	16.04	12.27	-23.46%
Dallas	4.18	3.10	-25.74%
San Antonio	8.82	6.27	-28.91%
NY	13.28	9.22	-30.57%
San Francisco	7.48	5.06	-32.39%
San Diego	14.19	8.82	-37.87%
LA	15.76	9.59	-39.12%
San Jose	8.75	4.97	-43.21%
Philadelphia	27.92	11.25	-59.70%

Table 3. Monthly average of NO_2 from continuous sensors on a road segment

The stay-at-home order resulted in a significant drop in VMT in the 15 counties in this study (Fig 1). For the seven cities where traffic volume data was available, the drop in weekday volume correlates with the decrease in NO_2 –an expected but nevertheless significant finding (Fig. 2), with the exception of San Jose, California. The relationship between traffic volume and NO_2 on the weekends is weaker (Fig. 3).

Most of the tropospheric NO_2 data from the 15 cities shows a decline in March and April 2020 as compared to 2019 (Table 4), with the month of March resulting in the highest aggregated decline of 34.5% (Fig. 4). New York showed the highest unit decline in March, and Houston showed the highest unit decline in April (Table 4; Figs. 5, 6)— both cities experienced the greatest unit decline during these months. Raster images from these two cities visualize this decline (Fig. 7).

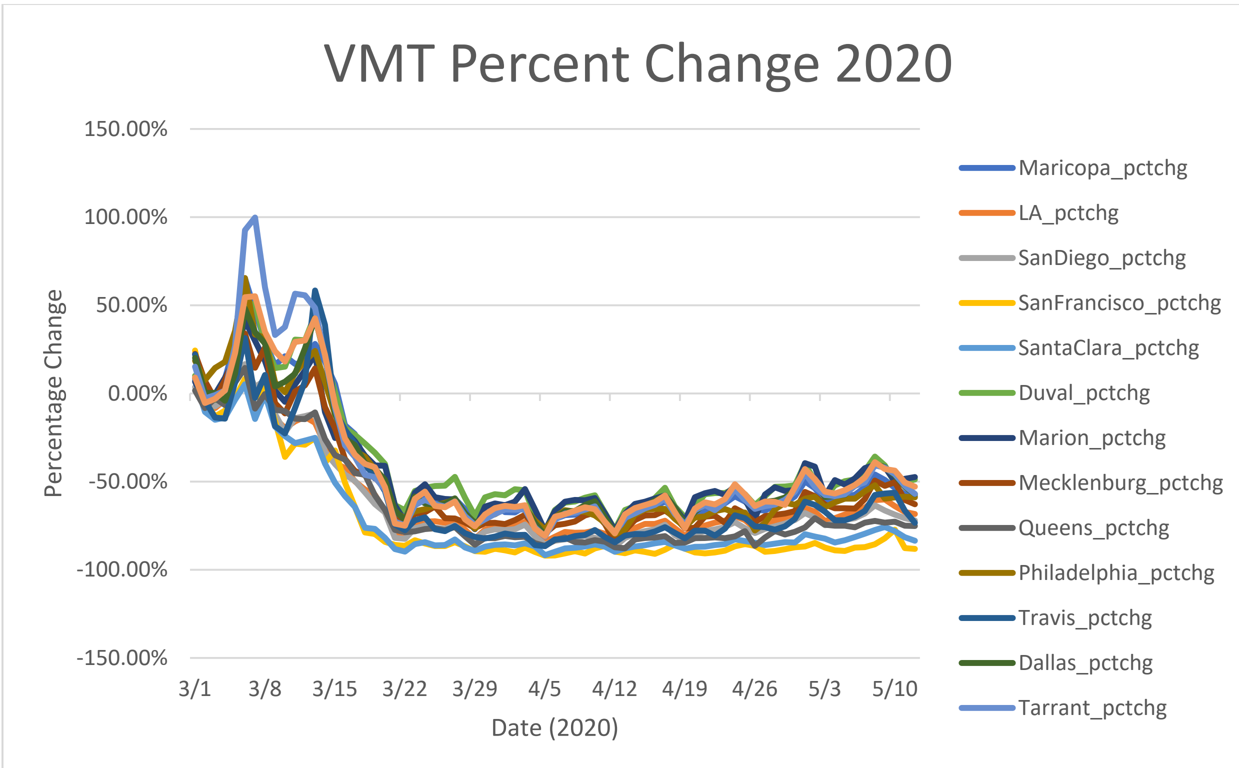

Fig 1. StreetLight Data for the 15 counties 2020.

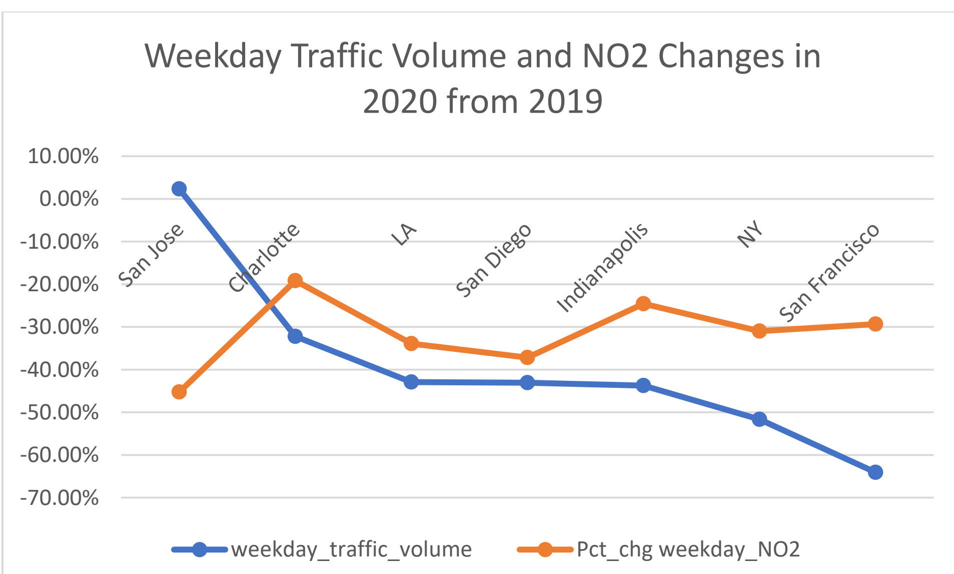

Fig 2. Continuous Traffic volume and NO2 sensors on weekdays from sites in 7 cities

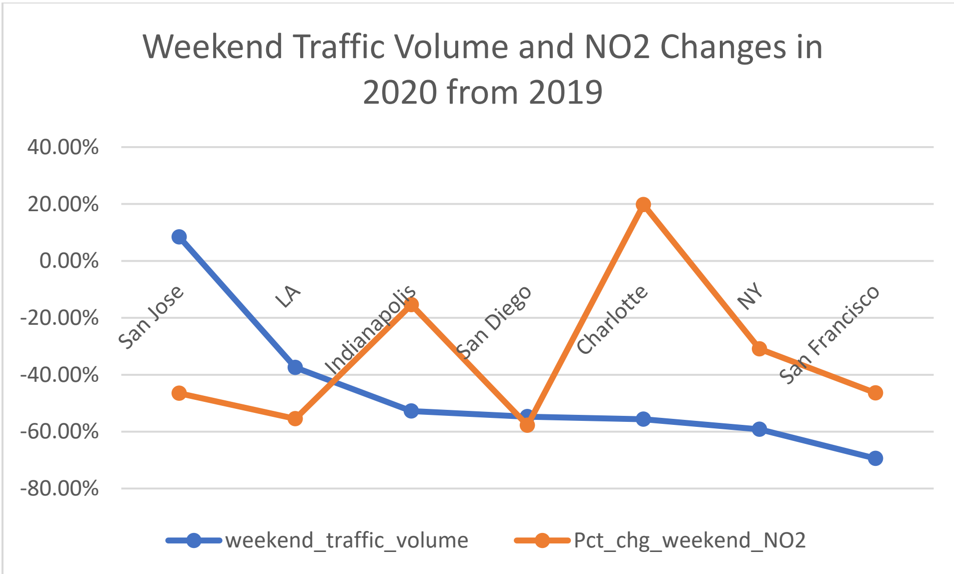

Fig 3. Continuous Traffic volume and NO2 sensors on weekends from sites in 7 cities

City	January_Tropo NO_2	February_Tropo NO_2	March_Tropo NO_2	April_Tropo NO_2
NY	16.03%	-12.35%	-48.19%	-30.85%
LA	-10.46%	77.00%	14.82%	-0.81%
Houston	6.01%	-3.27%	-57.00%	-59.33%
Phoenix	49.38%	-7.62%	14.86%	-7.14%
Philadelphia	20.67%	-13.53%	-29.19%	-21.41%
San Antonio	17.38%	-19.34%	-44.69%	-29.40%
San Diego	62.84%	16.12%	-48.40%	-36.36%
Dallas	10.21%	-11.44%	-30.10%	-23.79%
San Jose	17.87%	24.70%	-62.26%	-37.84%
Austin	24.96%	-25.61%	-38.21%	-19.15%
Jacksonville	-5.59%	-9.60%	18.01%	0.33%
Fort Worth	22.04%	-0.28%	-26.44%	-18.55%
San Francisco	20.82%	35.79%	-47.19%	-38.64%
Charlotte	7.65%	-6.57%	-26.68%	-47.42%
Indianapolis	30.02%	-22.02%	-16.23%	-14.18%

Table 4. GOME-2 Tropospheric NO_2 changes between January-April 2019 and 2020

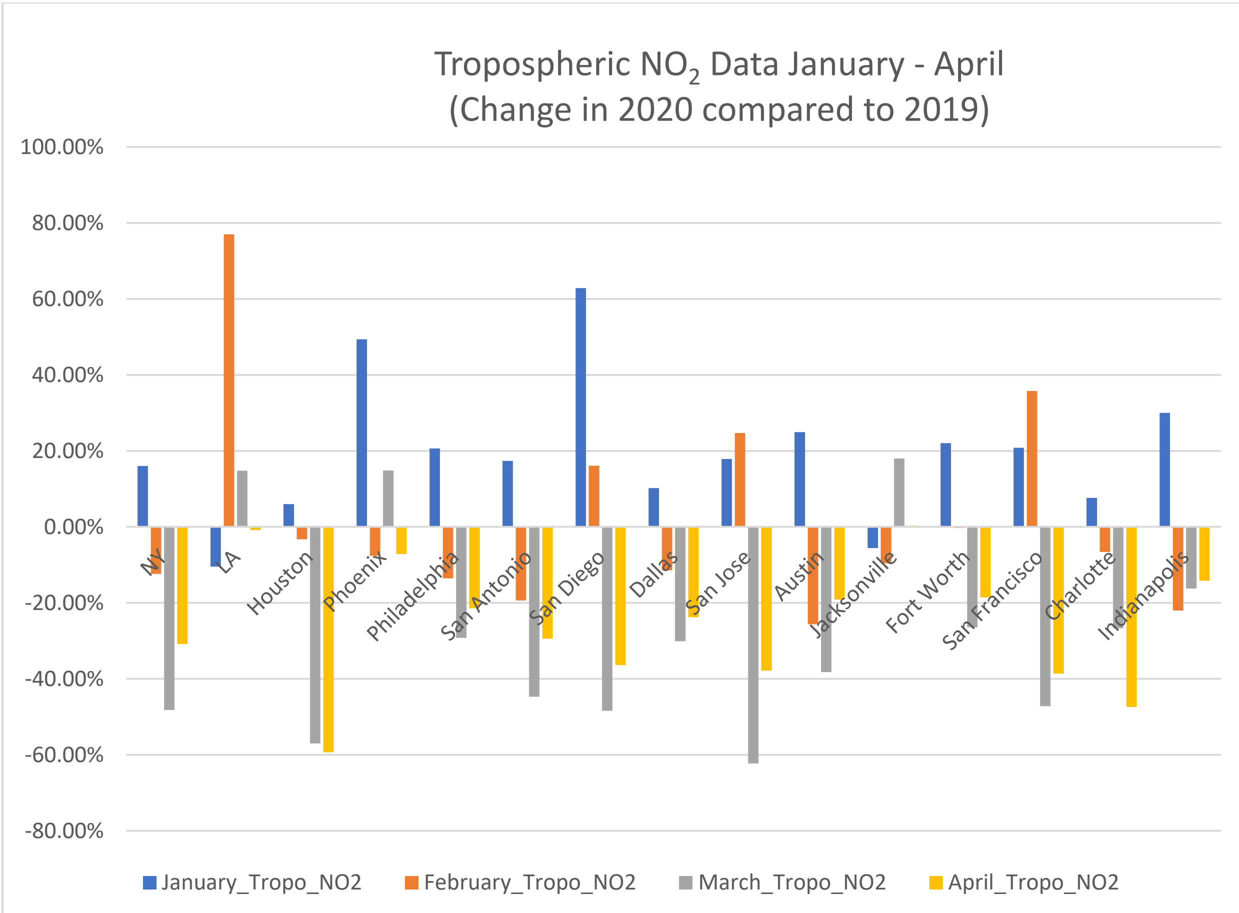

Fig 4. Tropospheric change comparison 2020 to 2019

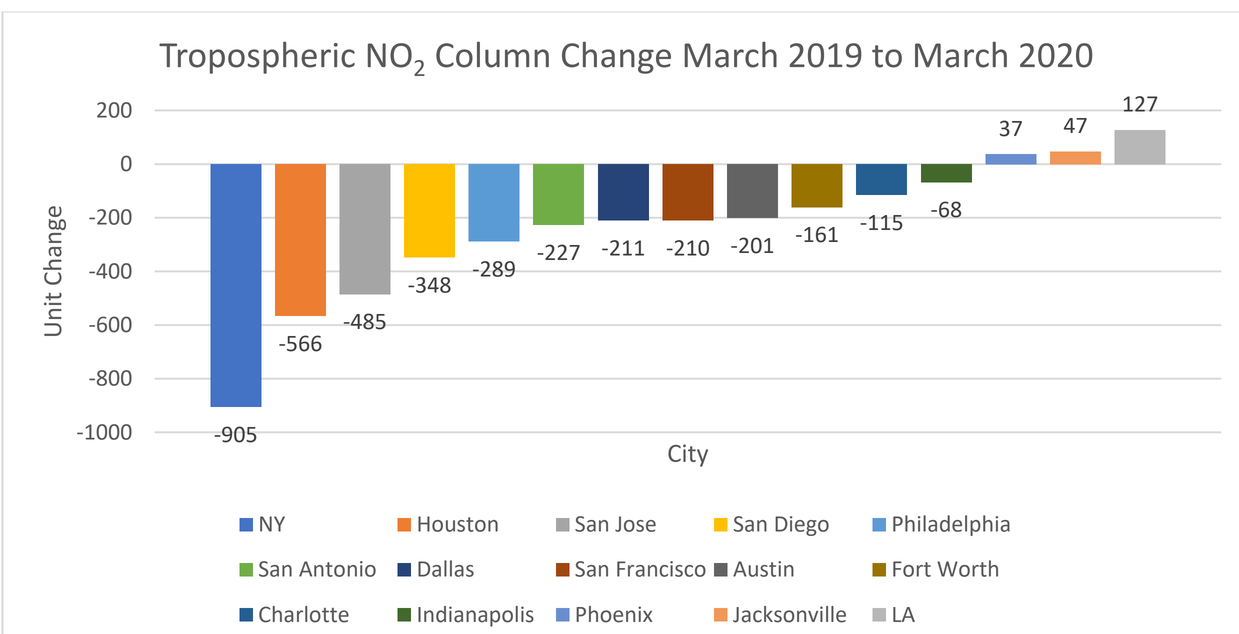

Fig 5. Tropospheric NO2 change from March 2019 to March 2020

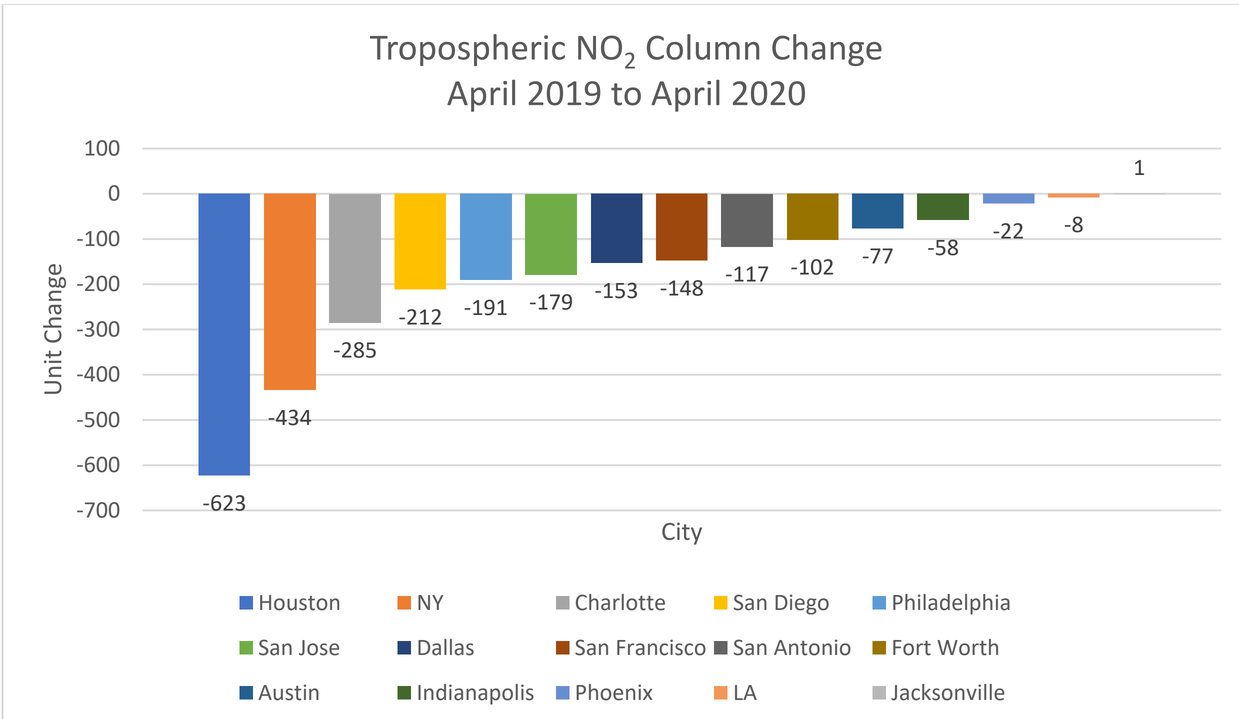

Fig 6. Tropospheric NO2 change from April 2019 to April 2020

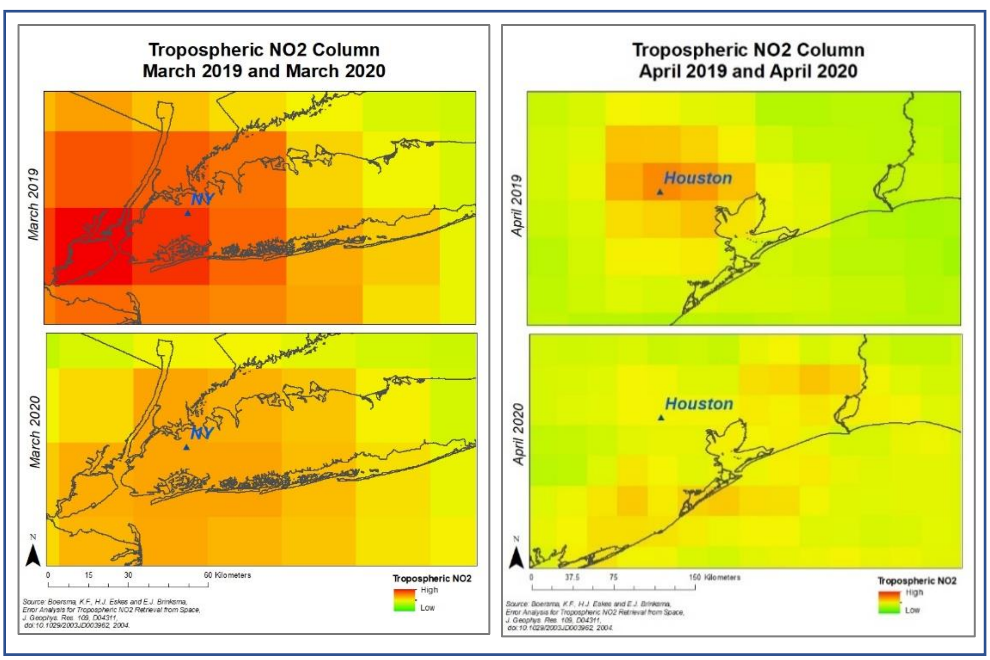

Fig 7. Tropospheric NO_2 change in NY and Houston from March 2019 to March 2020

Health data at the county level from USAFacts and ALA indicates that in 2018, Marion County (the City of Indianapolis consolidated the entire county, thus county health data is at the same population scale as city data) had the highest percent of COPD and lung cancer cases, which are highly correlated at 0.84 (Table 6 and Table S1). Marion County ranked 4th highest in percent asthma cases and 2nd highest in percent pediatric asthma cases (Table S2). Percent adult asthma has a high correlation of 0.57 with percent COVID-19 cases and 0.42 with normalized VMT (Table S3).

County	City	pct_copd	pct-lungcancer
Marion	Indianapolis	6.35%	0.07%
Duval	Jacksonville	5.78%	0.06%
Mecklenburg	Charlotte	5.61%	0.07%
Maricopa	Phoenix	5.25%	0.04%
Philadelphia	Philadelphia	4.89%	0.06%
Queens	NY	4.52%	0.06%
Bexar	San Antonio	4.48%	0.05%
Tarrant	Fort Worth	4.45%	0.05%
Dallas	Dallas	4.33%	0.05%
Travis	Austin	4.31%	0.05%
Harris	Houston	4.28%	0.05%
San Francisco	San Francisco	3.85%	0.04%
Los Angeles	LA	3.55%	0.04%
San Diego	San Diego	3.54%	0.04%
Santa Clara	San Jose	3.53%	0.04%

Table 6. Percent COPD and Lung-Cancer

The five highest correlations among the health and data were percent COVID-19 cases, percent COVID-19 deaths, VMT normalized by area of the counties, asthma, and tropospheric NO_2 extracted from GOME-2 pixel values (Table S4, S5, S6).

COVID-19 data indicates that during our study period, COVID-19 case rates and death rates in Marion County were both 3rd highest (Table S7, S8). The percentage of people with adult asthma shows the highest correlation with cases and death related to COVID-19 (Table S9), and correlations of mean NO_2 values indicate that it has the second highest positive correlation (0.32) with asthma cases in the study region (Table S10).

4. Discussion

High vehicular emissions can result in corridors of heavy pollution (Redling et al., 2013) in rural and urban regions. If left un-examined this can have increased adverse health effects on the population in the region, thus worsening conditions like respiratory disease, cardiovascular disease, and cancers, and even causing premature mortality (Lamsal et al., 2013; Filippelli et al., 2020). Findings in our study are consistent with other research which shows that NO_2 pollution is linked with increased asthma events in predominantly urban areas (Achakulwisut et al., 2019). Despite uncertainties from co-pollutants, short term exposure to NO_2 results in a likely causal relationship between it and ischemic heart disease (IHD) (Cesaroni Giulia et al., 2013; Stieb et al., 2020), and a 20 ppb increase in NO_2 results in increase in 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).

Most states in the U.S. started their stay-at-home order close to the third week in March of 2020. All the cities in this study except Jacksonville, FL significantly declined in NO_2 emission data from the continuous sensors in the road segments. The Jacksonville case was likely a result of a delayed start to the stay-at-home order in Florida, or perhaps too great of a mismatch between the location of the NO_2 monitor and the traffic volume sensor. When ground level data lacks consistency, tropospheric NO_2 satellite data, even with a geometric pixel resolution of 60 x 30 km^2, can be utilized in a meaningful way to examine various regions. GOME-2 data here also shows Jacksonville with the highest increase of 18% in tropospheric NO_2 column in March 2020, but in April 2020 it decreases down to almost the same levels as 2019, when most cities in the U.S. followed the stay-at-home orders. It is important to keep the difference in spatial resolution in mind when comparing ground level sensor data to satellite measurements (Drosoglou et al., 2017).

In comparing traffic volume and NO_2 emissions in 7 of the 15 cities we find traffic volume reduction and NO_2 emissions following a similar trend of substantial declines during weekdays, with the exception of San Jose. Since the traffic volume sensors and the NO_2 sensor are not co-located, we need to be careful in pairing the two sets of data. For a comprehensive examination, VMT can also be used as a proxy to NO_2 emissions or in conjunction with ground level sensor. It is important to note that meteorological conditions like temperature, wind speed, relative humidity, and precipitation which play a role in transport of atmospheric gases (Tobías et al., 2020) and particles were not considered in this analysis.

Overlaying available health data from ALA and USAFacts, we find that Queens (NY) had the highest case rate and death rate from COVID-19. Marion County (Indianapolis) was third in place for both at 0.47% and 4.74%. VMT (normalized by area of each county) has the highest correlation of 0.71 with COVID-19 case rate and 4th highest at 0.42 with percent adult asthma cases (Table S4) which in turn has a 0.58 correlation with percent COVID-19 cases (Table S9). Correlations of percent COVID-19 case rate, death rate, and VMT normalized by area, and ground level NO_2 all include asthma and tropospheric NO_2 values.

Disability Adjusted Life Years (DALYs) can be calculated based on population exposure to a number of pollutants (e.g., Landrigan et al., 2017), including criteria air pollutants such as ozone and PM2.5. For the purposes of this study using NO2 only, and for a short window of time during which NO_2 decreases, DALY calculations are not appropriate. We assume that the decreases would have to be substantial and long-lived to yield a life-time health benefit, but our results do point to a future for many US cities where improved population health due to a decrease in air pollution is achieved through electrifying vehicular fleets and improving industrial emission controls.

5. Conclusion

These results reveal a number of critical relationships between traffic volume, local emissions of NO_2, and the pre-existing health conditions of those most heavily impacted by air pollution, which may make them more susceptible to the more severe presentation of COVID-19 disease:

1. A substantial decline in NO_2 can be driven largely by policy—in this case, crisis policy involving virtually locking down vehicular traffic in cities.

2. Many urban areas have substantial percentages of the population with pre-existing conditions, potentially linked to air pollution exposure, which may make them more susceptible to severe COVID19 disease.

3. Linking NO_2 data derived from ground-based and satellite-borne sensors is useful for filling in key spatial data gaps and for contextualizing the sparse ground-level data with more spatially integrative satellite observations.

The silver lining provided by shut-down related air quality improvements are likely temporary, but lay bare the reality that air pollution likely makes inhabitants of some cities quite vulnerable to those very co-morbidities that exacerbate COVID-19 disease.

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Conflicts of Interest:

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

Data Policy:

The source data for NO_2 are publicly available through state's environmental management/protection portals, with all data being taken from EPA-grade sensors. Vehicle traffic density data 7 of the 15 cities is publicly available, reported by Department of Transportation's continuous sensor on a roadway segment in the respective cities. Aggregate VMT data for the 15 counties is publicly available via StreetLight Data (https://www.streetlightdata.com/our-data/). Health data is publicly availability via the Estimated Prevalence and Incidence of Lung Disease data from American Lung Association (ALA) was accessed. This data estimation is available at a county level and is based on a Behavioral Risk Factor Surveillance Survey conducted in 2017 and 2018 Centers for Disease Control's (CDC) joint report with other state and national registries (https://www.lung.org/research/trends-in-lung-disease/prevalence-incidence-lung-disease). Additionally, county-level COVID-19 cases and death data was accessed from USAFacts (https://usafacts.org/), a not-for-profit organization providing U.S. government data. Tropospheric NO_2 column data from the Global Ozone Monitoring Experiment-2 (GOME-2 (METOP-B)) satellite is available upon request from www.temis.nl.

Contributions to this work

Heitzelman and Filippelli conceptualized this work, performed analyses, and wrote the manuscript. Lulla assisted with statistical analysis and tropospheric NO_2 satellite pixel analysis.

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