Environmental Pollution 285 (2021) 117451

Contents lists available at ScienceDirect

Environmental Pollution

journal homepage: www.elsevier.com/locate/envpol

On the impact of the COVID-19 pandemic on air quality in Florida☆

Marwa M.H. El-Sayed [a,*], Yasin F. Elshorbany [b], Kirsten Koehler [c]

[a] Department of Civil Engineering, Embry-Riddle Aeronautical University, Daytona Beach, 32114, USA
[b] College of Arts & Sciences, University of South Florida, St. Petersburg, FL, 33701, USA
[c] Department of Environmental Health and Engineering, Johns Hopkins University, Baltimore, MD, 21205, USA

ARTICLE INFO

Keywords:
COVID-19 lockdown
Vehicular emissions
Power generation
Ground-level measurements
Criteria pollutants

ABSTRACT

Since early 2020, the world has faced an unprecedented pandemic caused by the novel COVID-19 virus. In this study, we characterize the impact of the lockdown associated with the pandemic on air quality in six major cities across the state of Florida, namely: Jacksonville, Tallahassee, Gainesville, Orlando, Tampa, and Miami. Hourly measurements of $PM_{2.5}$, ozone, NO_2, SO_2, and CO were provided by the US EPA at thirty sites operated by the Florida Department of Environmental Protection during mid-February to mid-April from 2015 through 2020. To analyze the effect of the pandemic, atmospheric pollutant concentrations in 2020 were compared to historic data at these cities during the same period from 2015 to 2019. Reductions in NO_2 and CO levels were observed across the state in most cities and were attributed to restrictions in mobility and the decrease in vehicle usage amid the lockdown. Likewise, decreases in O_3 concentrations were observed and were related to the prevailing NO_x-limited regime during this time period. Changes in concentrations of SO_2 exhibited spatial variations, concentrations decreased in northern cities, however an increase was observed in central and southern cities, likely due to increased power generation at facilities primarily in the central and southern regions of the state. $PM_{2.5}$ levels varied temporally during the study and were positively correlated with SO_2 concentrations during the lockdown. In March, reductions in $PM_{2.5}$ levels were observed, however elevations in $PM_{2.5}$ concentrations in April were attributed to long-range transport of pollutants rather than local emissions. This study provides further insight into the impacts of the COVID-19 pandemic on anthropogenic sources from vehicular emissions and power generation in Florida. This work has implications for policies and regulations of vehicular emissions as well as consequences on the use of sustainable energy sources in the state.

1. Introduction

In the beginning of the year 2020, the world was confronted with the COVID-19 outbreak, which was declared a pandemic by the World Health Organization (WHO) in February 2020 (WHO, 2020). The first cases of this novel virus were reported in Wuhan City, China in December 2019 (Zhu et al., 2020) but rapidly spread around the world in early 2020 (WHO, 2020). A year later, the pandemic was further escalating with third waves occurring in many countries around the globe. By mid-February 2021, there were already ~2.4 million deaths, and ~109.4 million cases on a global scale (WHO, 2021).

Most countries worldwide have taken immediate measures and enforced quarantine to reduce the spread of the virus. With most of the world in a mandatory quarantine, the COVID-19 pandemic has influenced the mobility and traffic loads in most cities all over the world (e.g., Parr et al., 2020). Further, changes in the patterns of energy consumption and generation were reported (Le Quéré et al., 2020). From an environmental perspective, the mandatory lockdowns and reductions in economic activity associated with the COVID-19 pandemic have reportedly improved environmental conditions in many countries. Several studies report improvements in water quality (Nir-oumand-Jadidi et al., 2020), reductions in greenhouse gas emissions such as carbon dioxide (Le Quéré et al., 2020; Zheng et al., 2020; Nguyen et al., 2021), and enhanced skyglow (Jechow and Hölker, 2020) due to reduced air pollution (Ventera et al., 2020).

Globally, air pollution is responsible for the death of approximately 7 million people on an annual basis (WHO, 2016). In the United States, the Environmental Protection Agency (US EPA) monitors six atmospheric pollutants, named criteria pollutants, through the National Ambient Air Quality Standards (NAAQS) due to their detrimental impacts on human

☆ This paper has been recommended for acceptance by Da Chen.

* Corresponding author.
E-mail address: marwa.elsayed@erau.edu (M.M.H. El-Sayed).

https://doi.org/10.1016/j.envpol.2021.117451
Received 4 March 2021; Received in revised form 14 May 2021; Accepted 21 May 2021
Available online 22 May 2021

health as well as the environment (Esworthy, and McCarthy, 2013). These include particulate matter with aerodynamic diameter less than 2.5 μm ($PM_{2.5}$), nitrogen and sulfur dioxides (NO_2 and SO_2, respectively), carbon monoxide (CO), and ozone (O_3). NO_2 is a primary pollutant that is mainly produced from vehicular emissions, and has therefore exhibited wide reductions during the lockdowns (Hoang et al., 2021), as evident from ground-level measurements (Berman and Ebisu, 2020; Zangari et al., 2020) and remote sensing data (Karaer et al., 2020; Elshorbany et al., 2021). CO is also a primary pollutant, emitted directly due to combustion, that has displayed a decline in its concentrations during the lockdowns (Chen et al., 2020). SO_2 is generated mostly from fossil fuel burning in power generation leading to inconsistent patterns during the lockdown (Bekbulat et al., 2021) as a result of variations in power generation during this period. Particle pollution has been strongly and consistently shown to be associated with harms to human health due to short- (Achakulwisut et al., 2019) and long-term exposures (Burnett et al., 2018; Lelieveld et al., 2020). Overall, studies have suggested a decrease in $PM_{2.5}$ concentrations as a result of the lockdown (e.g., Tanzer-Gruener et al., 2020; Le et al., 2020). Finally, O_3 is a secondary photochemical pollutant that is formed from NO_2 photolysis as a result of oxidation of volatile organic compounds (VOCs) in the presence of NO. During the lockdown, concentrations of O_3 have increased in many cities around the globe (Sicard et al., 2020), possibly due to prevailing high-NO_x photochemical regimes found in many urban areas (Elshorbany et al., 2009b).

Air quality in the state of Florida is of interest because almost 25% of the state's population are elderly and may represent a particularly vulnerable group for exposures to atmospheric pollutants (Delfino et al., 2013). The state has a population of almost 20 million people and its population growth rate is amongst the fastest in the US (US Census Bureau, 2019). For this study, we selected six cities that are diverse in terms of their location, population, and air pollution sources. Jacksonville is an industrial city that lies on I-95 highway that connects northern and southern regions of the eastern US and has a population of 890,467 people (~1.5 in the metropolitan area). Miami is in southern Florida, a well-known urban city and a tourist attraction with a population of 454,279 people (~2.72 in the metropolitan area). Orlando and Tampa both lie in central Florida, while the former is inland, the latter is a coastal city, with city populations of 280,832 and 387,916 (~2.51 and 3.10 in the metropolitan areas), respectively. Tallahassee, with a population of 191,279 people, lies on the Gulf of Mexico. Gainesville is the least populated and has a population of 132,127 people and is an inland city. Overall, Jacksonville, Tampa, Orlando, and Miami are located within the biggest metropolitan areas in the state. Tallahassee represents the capital of Florida, and with Gainesville, provides a representation of smaller sized cities in the state. The cities also span from Jacksonville and Tallahassee near the Georgia border to Miami, near the southern extent of the state. Based on the state of the air report issued by the American Lung Association, O_3 and $PM_{2.5}$ are within unhealthy levels in several of these Florida cities (American Lung Association, 2020) posing a danger due to long-term exposure (Burnett et al., 2018; Lelieveld et al., 2020).

On March 9, 2020, the Florida Governor issued an Executive Order, declaring the state of emergency due to COVID-19 virus. Shortly after, during March 12th to 17th, all restaurants, amusement parks, bars, and stores were closed to control the spread of the virus, lasting until mid-April in most of the regions in Florida. As a result, a few studies have attempted to characterize the impact of the COVID-19 pandemic lockdowns on air quality in the state. However, these were conducted either by using remote sensing data (Elshorbany et al., 2021; Karaer et al., 2020), or on a relatively low temporal resolution (Bekbulat et al., 2021), or focused primarily on few criteria pollutants (e.g., Karaer et al., 2020). Hence, these studies lack the capability to explain the overall processes that govern air quality on a city level. This high scale characterization is especially important in human health exposure studies.

In this paper, we investigate the effect of the COVID-19 pandemic lockdowns on air quality in the state of Florida. Using ground-level regulatory monitoring measurements, we investigate daily pollutant concentrations in six major cities in Florida before and during the pandemic in 2020, and compare levels of atmospheric pollutants in 2020 during the lockdown to their corresponding historic averages in the last five years from 2015 to 2019. Potential causes of changes in pollutants concentrations are investigated. We use this natural experiment to provide insight into the potential drivers responsible for the formation of gaseous and particle atmospheric pollutants in Florida including vehicular and power generation emissions. To the best of our knowledge, this is the first study to characterize the impacts of the COVID-19 pandemic on five different criteria pollutants at high spatial and temporal resolutions in the southeastern US.

2. Methods

2.1. Measurement locations

Data was collected from thirty monitoring stations in 16 counties around six metropolitan areas in Florida. These cities represent northern Florida: Jacksonville, Tallahassee, and Gainesville; central Florida: Orlando and Tampa, and southern Florida: Miami. Fig. S1 depicts all the sites used in the analyses. A full list of sites at each city including the longitude, latitude, the site's Air Quality System identification number (AQS ID#) in addition to the specific pollutants measured at this site is shown in Tables S1 through S6.

2.2. Criteria pollutants

Hourly $PM_{2.5}$, CO, O_3, NO_2, and SO_2 measurements from 30 monitoring stations were acquired from the US EPA (https://aqs.epa.gov/api) from mid-February to mid-April for the years 2015–2020. Data were aggregated by city and pollutant, and 24-h averages were calculated for each day either in 2020 or as an average across 2015–2019. Analyses conducted throughout this study are based only on periods where no precipitation was reported (i.e., 97% of hours). This method was adopted to ensure that concentration changes were not due to dilution as a result of rainfall. The study period was divided into two periods lasting for one month each, namely the "Pre-lockdown" and the "Lockdown" periods corresponding to February 15th to March 15th and March 15th to April 15th, respectively. The former pertains to the period prior to the lockdown and the latter was chosen to capture the period in which the state was under lockdown. The Lockdown period was chosen because it corresponded to a complete shutdown across the state, after which central and northern regions of Florida were not completely closed, whereas there was still a complete shutdown in the southern portion of the state with higher infection rates (Glanz et al., 2020).

2.3. Ancillary measurements

Meteorological data: Wind speed, wind direction, and precipitation were acquired from the Florida Automated Weather Network (FAWN) operated by University of Florida, Institute of Food and Agricultural Sciences (https://fawn.ifas.ufl.edu/; Lusher et al., 2008) at their 44 stations across the state from mid-February to mid-April for the years 2015–2020 at their corresponding sites. Point measurements were reported every 15 min. Wind speed and direction data acquired from multiple sites (within ~10 km of the EPA monitoring sites) per city were 24-h averaged and were used to create the bivariate polar plots. Precipitation data was used to determine periods of rainfall.

Power generation data: The net power generation data of Florida from different sources were acquired by the International Energy Agency (IEA, 2020) at https://www.eia.gov/realtime_grid/and https://www.eia.gov/environment/emissions/state/. These were used to determine trends in power generation to investigate their link to atmospheric pollutants.

Apple mobility data: The transportation data were acquired by the Apple Mobility Trends data (Apple Mobility Trends Reports, 2020) at https://www.apple.com/covid19/mobility/. These were used to determine trends in vehicle usage to characterize the impact of mobility on atmospheric pollutants.

2.4. Bivariate polar plots

Bivariate polar plots were plotted using R package entitled 'openair' (Carslaw and Ropkins, 2012; Carslaw, 2013) which associates concentrations of a pollutant to local wind speed and wind direction. Using smoothing techniques, both wind speed and direction are modeled as a continuous surface to determine the wind directions and speeds associated with higher concentrations at a specific location. A detailed explanation of creating these pollution plots is reported elsewhere (Carslaw et al., 2006; Carslaw, 2013). In our case, the inputs to the model included average pollutant concentrations together with wind speed and wind direction pertaining to a specific city from various sites located at that city.

2.5. Statistical analyses

The statistical significance of the changes observed in the daily average concentrations of the five pollutants in 2020 compared to historic data (daily average of data from 2015 to 2019) was tested separately for each city and pollutant using a linear mixed-effects model (LME model) to account for possible autocorrelation in the sampling data. Data were assessed for normality and transformed, as needed, to meet model assumptions (see Supplemental Information for more detail). Statistical analyses were conducted in MATLAB (MathWorks, Inc., Natick, MA, Version R2018A).

3. Results and discussion

3.1. Effect of lockdown on atmospheric pollutants

An overview of meteorological data at the six cities including precipitation, relative humidity, and wind speed during the Lockdown period is shown in Figs. S2, S3, and S4, respectively.

To evaluate the effect of the lockdown due to the COVID-19 pandemic on air quality in six cities in Florida, boxplots of daily criteria pollutant concentrations during the Lockdown period in 2020 were compared to their five-year (2015–2019) average observations during the same time period (Fig. 1). The latter period henceforth is referred to as the "Lockdown_Historic" and the former period is referred to as the "Lockdown". Based on the results of the LME model, we found that for most cities and pollutants, there was a statistically significant change in concentrations in 2020 compared to the Historic period during the Lockdown (Table S7). Those cities and pollutants for which there was not a significant change are noted on Fig. 1. To provide additional evidence that changes observed were associated with the lockdown, we have also compared concentrations of pollutants during the Pre-lockdown period in 2020 to their corresponding five-years historic concentrations (2015–2019; see Table S8). We observed fewer statistically significant changes in pollutant concentrations between the Pre-lockdown periods in 2020 compared to the historic period, suggesting that the changes in concentrations during the Lockdown period are attributed primarily to the impact of the lockdown on air quality. To gain a better insight into the magnitude of the changes in pollutant concentrations we observed across Florida during the lockdown, we calculated the percent changes in median daily pollutant concentrations in each city over the lockdown period in 2020 compared to the historic period, as shown in Fig. 1g.

Fig. 1a shows that median NO_2 concentrations have decreased at all sites in northern, central, and southern Florida during the lockdown in 2020 compared to the historic period (also see Table S7). On average, the observed decrease in NO_2 concentrations across Florida was 25.2 ± 9.2% (±1σ, where σ is the standard deviation of the percent change between cities; Fig. 1g). Similarly, CO concentrations demonstrated a decrease during the lockdown compared to the historic period and a wider range of decreases across the entire state (Fig. 1b). The largest decreases in CO concentrations were observed in central and southern Florida in Orlando (27.3%) and Miami (24.2%), while the decreases in northern Florida were less than 15% (Fig. 1g). Differences observed in NO_2 and CO levels between cities are likely due to the population differences amongst the cities, leading to differences in mobile emissions. This might explain why the reductions in NO_2 and CO were most pronounced in central and southern Florida, the two regions with the highest population in the state. Additionally, the stay-home orders were not strict in all cities, for example, the orders were stricter in Miami as opposed to Orlando (Glanz et al., 2020), hence the stronger reductions observed in the south compared to the central parts of the state. A decrease of both NO_2 and CO was observed during the COVID-19 pandemic in several countries around the world such as Kazakhstan (Kerimray et al., 2020), Brazil (Nakada and Urban, 2020), India (Sharma et al., 2020), and Italy (Collivignarelli et al., 2020), due to reductions in the use of vehicles during the worldwide COVID-19 lockdowns. Similar decreases in NO_2 and CO levels were reported in Florida using ground level data (Shakoor et al., 2020).

Similarly, O_3 decreased at all sites in Florida during the Lockdown period compared to historic averages (Fig. 1c) by about 12.4 ± 3.1% across the state (Fig. 1g). These changes in O_3 concentrations due to the lockdown in Florida are different from what was observed for O_3 concentrations in many other locations outside of the US. For instance, O_3 concentrations increased in China (Li et al., 2020), India (Sharma et al., 2020), Brazil (Nakada and Urban, 2020; Dantas et al., 2020), Spain (Tobias et al., 2020), and Italy (Collivignarelli et al., 2020) despite the significant reductions in NO_2 concentrations in these locations. These results indicate that the secondary formation of ozone in Florida is NO_x-limited while it is predominantly VOC-limited in other reported regions (Elshorbany et al., 2021; Cazorla et al., 2020). These results are in accord with satellite data reporting similar decreases in NO_2, CO, and O_3 levels across Florida (Elshorbany et al., 2021).

Concentrations of SO_2 (Fig. 1d) exhibited a different spatial variability than NO_2, O_3, and CO. By comparing the median of SO_2 levels during the lockdown in 2020 to levels in the Historic period, a significant decrease was observed in Jacksonville and Tallahassee (44.1% and 52%, respectively) in northern Florida, opposed to an increase in central and southern Florida (87.2% in Tampa and 26.3% in Miami; 15.4% in Orlando, not statistically significant), during the Lockdown period compared to the Lockdown_Historic period (Fig. 1g). Worldwide, no clear spatial variability was reported for SO_2 levels in previous studies during COVID-19's lockdown. For instance, Li et al. (2020) observed a significant reduction in SO_2 levels, while other studies provide no evidence for any change in SO_2 concentrations, e.g., Italy (Collivignarelli et al., 2020), India (Sharma et al., 2020), and Spain (Tobias et al., 2020). Decreases in SO_2 were previously observed in Florida (Shakoor et al., 2020), but these values did not take into account the spatial variations we report herein.

Over the full lockdown, most cities showed no statistically significant difference in $PM_{2.5}$ concentrations compared to the Historic period; only Jacksonville showed a statistically significant increase in concentrations. However, $PM_{2.5}$ concentrations showed an interesting temporal distinction between the last two weeks of March and the first two weeks of April during the Lockdown period. $PM_{2.5}$ concentrations from the 15th to 30th March, and 1st to 15th April will be henceforth referred to as $PM_{2.5(March)}$ and $PM_{2.5(April)}$, and are shown in Fig. 1e and f, respectively. For $PM_{2.5(March)}$ concentrations, statistically significant reductions were observed in Miami (21.6%) and Tampa (16.6%), but concentrations significantly increased by 62.7% in northern Florida in Jacksonville (Fig. 1g). On the other hand, concentrations of $PM_{2.5(April)}$ increased at all cities with the highest increase of 128.7% observed in

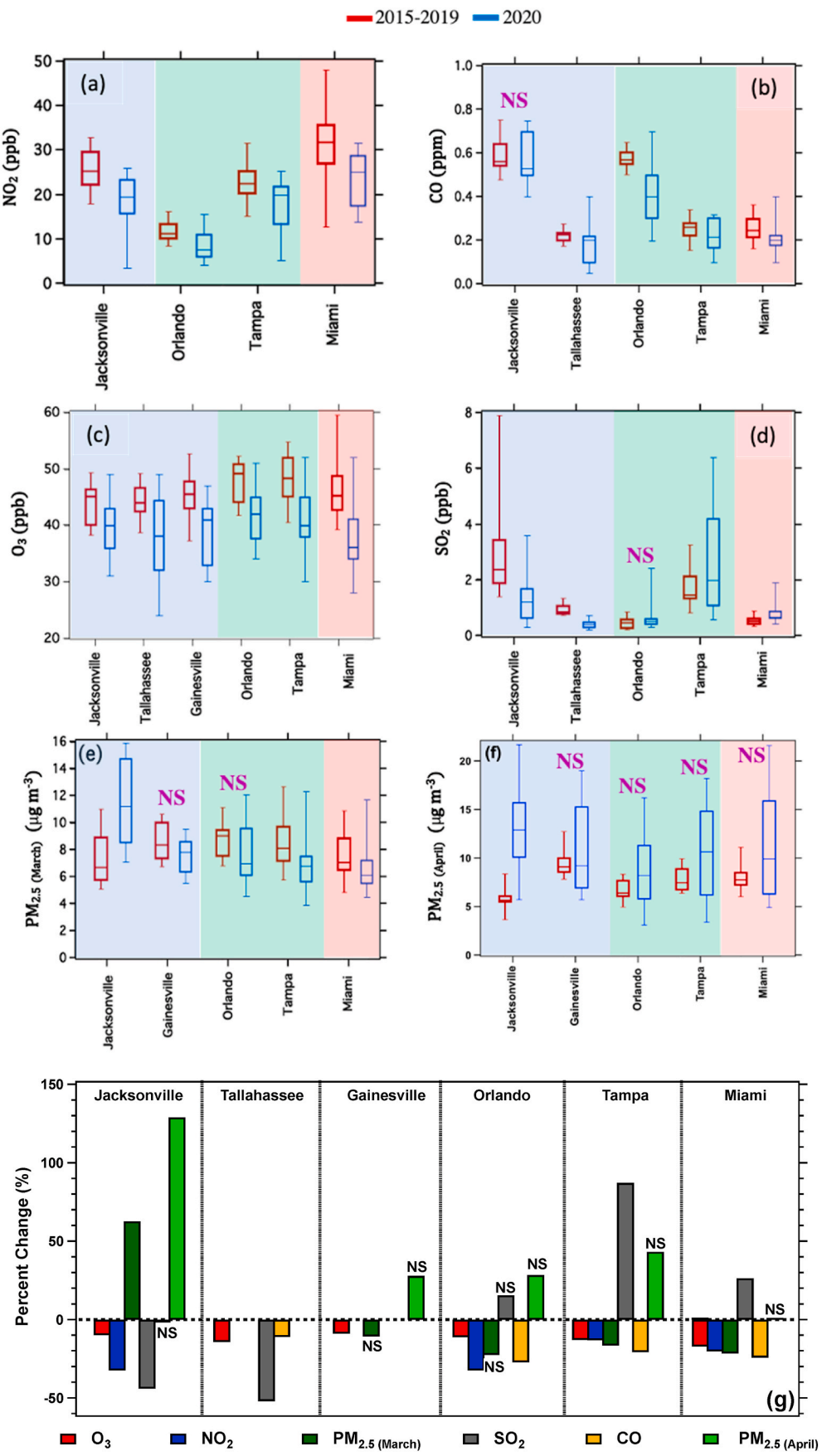

Fig. 1. Boxplots of daily (a) NO_2, (b) SO_2, (c) CO, (d) O_3, (e) $PM_{2.5(March)}$, and (f) $PM_{2.5\ (April)}$ concentrations in Jacksonville, Tallahassee, Gainesville, Orlando, Tampa, and Miami during 15th March to 15th April 2020, whenever data is available. For each site, median (horizontal line), 25th and 75th percentiles (lower and upper box values), as well as 5th and 95th percentiles (vertical lines) are shown. Boxplots in red color pertain to datasets in the "Lockdown_Historic" period as daily averages across 2015–2019 and blue boxplots are those corresponding to datasets in the "Lockdown" period in 2020. Blue, green, and red shading represent northern, central, and southern regions of Florida, respectively. (g) Percent change in median O_3, $PM_{2.5}$, NO_2, SO_2, and CO concentrations in all cities during the Lockdown period in 2020 compared to Lockdown_Historic concentrations. Note that $PM_{2.5}$ concentrations are divided into $PM_{2.5(March)}$ in dark green color and $PM_{2.5(April)}$ in light green color. NS: represents cities where a pollutant did not exhibit a statistically significant change in mean concentrations compared to the Historic period according to the LME model. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

Jacksonville followed by smaller and statistically insignificant reductions in the other cities (Fig. 1g). $PM_{2.5}$ concentrations displayed a decrease in most cities around the world as a result of the lockdown, although the decrease was more pronounced in China compared to that in Europe (Sicard et al., 2020; Chauhan et al., 2020).

The reason(s) for the increase in $PM_{2.5(April)}$ we observe herein is(are) unclear; however, it should be noted that the chemistry of $PM_{2.5}$ is complicated as it is affected by several factors (Kroll et al., 2020). Interestingly, while $PM_{2.5(March)}$ showed an inverse relation with SO_2, SO_2 was positively related to $PM_{2.5(April)}$ (Fig. 1g, Table S9). These observations may suggest that formation of $PM_{2.5(March)}$ sulfate aerosols was oxidant limited, i.e., abundant SO_2, which may be due to short range transport and local sources in central and southern Florida. This argument is supported by our previous observations of decreases in NO_2 concentrations across Florida while SO_2 concentrations were enhanced in central and southern regions, and the fact that $PM_{2.5}$ was correlated to SO_2 and NO_2 in the Lockdown and Pre-lockdown periods, respectively (Table S9). Conversely, the opposite behavior of SO_2 and $PM_{2.5}$ was observed during March in the north. On the other hand, $PM_{2.5(April)}$ increased everywhere in Florida which may have been related to increased emissions from local sources, such as power plants, long-range transport from other regions, as well as by westerly winds.

3.2. Factors affecting air quality amid lockdowns

In this section we investigate possible reasons for the changes we observed in the concentrations of the studied criteria pollutants. In what follows is a detailed investigation of each of these plausible scenarios.

3.2.1. Effect of pollution transport

Due to the disparities we observed in the behavior of $PM_{2.5}$ concentrations due to the lockdown in late March and early April, especially the inverse relationship between SO_2 and $PM_{2.5(March)}$, we further investigate the transport of pollutants as a potential explanatory factor, using Hybrid Single-Particle Lagrangian Integrated Trajectory model (HYSPLIT) back trajectories, bivariate polar plots, and wind analyses. The analyses will help understand the role of pollution transport on the spatial distribution of atmospheric pollutants in Florida.

We employed analyses of back trajectories using the HYSPLIT model. The Lockdown period was split into two periods: March 15th – 30th and April 1st – 15th, and 72-hr back trajectories were run for each day at each of the six cities (15 trajectories in each period, per city). As shown in Fig. S5, air mass transport exhibited two distinct behaviors in the two split periods. In central Florida, back trajectories in March were mostly originating from the Atlantic Ocean flowing through the Gulf of Mexico. In southern Florida, air masses in March originated only from the Atlantic Ocean. However, air masses impacting Jacksonville in March show some influence of long-range transport from other regions in the US. Air masses from the Atlantic Ocean are either clean or carrying Saharan dust (Holloway et al., 2003); however, our study period took place before the Saharan dust season, therefore we do not expect dust to contribute to our results. Northern Florida seems to be hugely impacted by air masses from southern and central Florida, while central Florida is impacted only by air masses from southern Florida and the Atlantic Ocean. These results may explain the elevated $PM_{2.5}$ concentrations in northern Florida during the Pre-lockdown period extending into the Lockdown period.

In April, on the other hand, in addition to air masses from the Atlantic Ocean, Fig. S5 shows influences of long-range transport from other western regions of the US (at least 5 out of 15 days at all cities) which corresponded to the highest daily average concentrations observed during this period. This could be the reason behind the increased $PM_{2.5}$ concentrations over all cities in Florida in April. While our study period did not involve major wildfires in the US (Cal Fire, 2020); however, wildfires seemed to have an impact on aerosol loadings on a global scale (Sanap, 2021). Detailed and more robust measurements must be conducted to address whether these influences were due to wildfire emissions.

Fig. 2 depicts the bivariate polar plots of O_3, $PM_{2.5}$, and NO_2 at northern, central, and southern Florida. CO and SO_2 data were insufficient to construct similar plots. Bivariate polar plots of $PM_{2.5}$ concentrations emphasize that concentrations in March were lower than those in April in 2020. April polar plots of $PM_{2.5}$ concentrations show that the highest concentrations (20–30 $\mu g\ m^{-3}$) were associated with winds from the south and southwest directions and for high wind speeds of up to 20 mph in Tampa, Orlando, and Jacksonville. In Miami, bivariate polar plots in April provide evidence for multiple $PM_{2.5}$ paths. One path is due to air masses from the south and southwest directions at wind speeds approximately 10 mph similar to the other cities, but an additional path originating from the north and northwest directions occurs at wind speeds of approximately 10 mph. These observations emphasize the impact of air pollution from southern Florida on central parts of the state as discussed above. This argument is supported by the relatively strong correlations in $PM_{2.5}$ concentrations between Miami and each of the following cities in central Florida: Orlando ($r = 0.59$) and Tampa ($r = 0.69$) (Table S10), and is also supported by Orlando and Tampa HYSPLIT back trajectories (Fig. S5), which pass through Miami before they impact cities in central Florida. It could be deduced from these observations that except for some air masses impacting central Florida from northern states and possibly Texas, central Florida might be largely affected by conditions in the south. Moreover, the impact of south and central Florida air masses on northern Florida cities, i.e., Jacksonville and Tallahassee were observed in March's back trajectories (Fig. S5). Hence, we cannot rule out the effect of transport of air masses from Miami as this seems to play a critical role in the air quality of central and northern Florida. Wind analyses reveal that $PM_{2.5}$ concentrations in April exhibited a positive correlation with wind speed in central and southern Florida (Figs. S6, S7, and S8), as wind speeds increase, concentrations of $PM_{2.5}$ increased as well, indicating a transport effect on $PM_{2.5(April)}$ levels.

O_3 concentrations display a regional pattern (Fig. 2) with higher concentrations of about 40 ppb observed at relatively high wind speeds and lower concentrations observed under stagnant conditions. The wind analyses in Orlando (Fig. S7), Tampa (Fig. S8), and Jacksonville (Fig. S9) show a negative relationship between O_3 and wind speed at these locations highlighting this regional phenomenon. These results are consistent with Florida's favorable conditions of high temperature and sunlight for high ozone levels (Elshorbany et al., 2009a). Similarly, the negative correlation between NO_2 concentrations and wind speed in Miami (Fig. S7) and Tampa (Fig. S8) indicates that NO_2 formation is mainly local, as expected from its short lifetime during the day.

3.2.2. Increase in power generation due to residential usage

We have shown in the previous sections that SO_2 levels were enhanced in central and southern Florida during the lockdown compared to reduced levels observed in northern Florida. These results have warranted the investigation of the sources of SO_2. In Florida, SO_2 is produced primarily from fossil fuel combustion at power plants (EPA, 2020). Due to lack of data in years prior to 2019, Fig. 3 shows a comparison of the net power generation in the state of Florida during the Pre-lockdown and Lockdown periods in 2020 and their corresponding values in 2019 from different energy sources including fossil fuel sources (i.e., coal, petroleum, and natural gas) and more sustainable sources (including solar, hydro, and nuclear energy). There are two important points that could be deduced from Fig. 3. First, the total net generation has revealed an increase of 13.7% during the Lockdown period in 2020 compared to the same period in 2019. Second, a negligible increase (0.2%) was observed during the Pre-lockdown period as shown in Table S11 when compared to its corresponding period in 2019. Put together, these two observations demonstrate that the enhancements observed during the lockdown in 2020 were not observed in the same period in 2019 and that this was not a trend observed prior to the

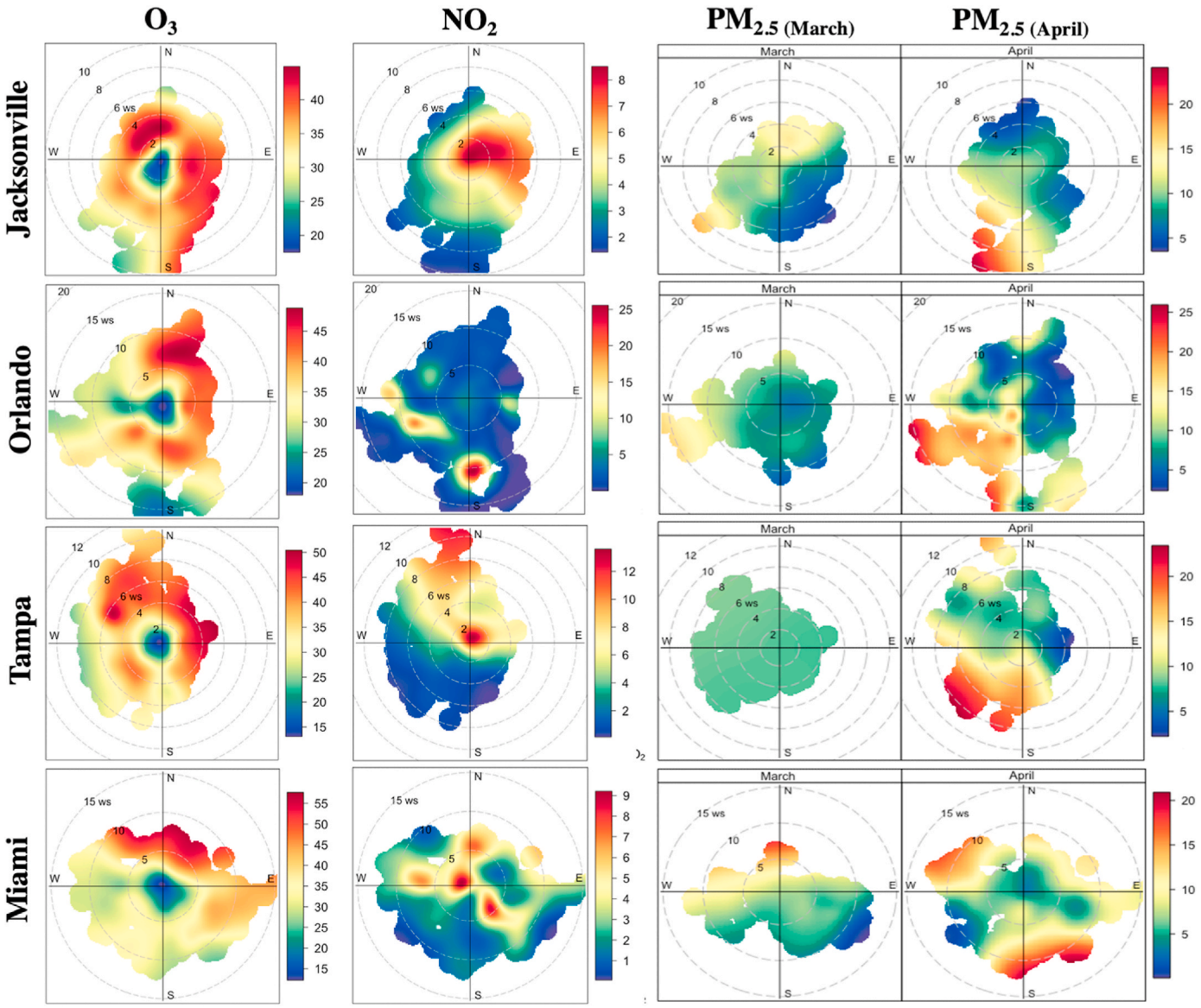

Fig. 2. Bivariate polar plots of mean concentrations of O_3, NO_2, $PM_{2.5(March)}$, and $PM_{2.5(April)}$ in Jacksonville, Orlando, Tampa, and Miami as a function of wind speed (ws, in mph) and wind direction (N: north, S: south, E: east, and W: west).

lockdown period in 2020 either. This could be due to higher temperature anomalies during the first two weeks of the lockdown in 2020 compared to those in 2019 in Jacksonville, Orlando, Tampa, and Miami in 2020 (Fig. S10). Consequently, due to elevated temperatures and extended periods spent indoors, the power generation has increased in 2020 compared to 2019 likely due to increased residential cooling. However, a thorough investigation is required to test this hypothesis given the two contradicting processes: (1) less industrial power consumption and less cooling in offices, etc. and (2) more power consumption in residential buildings.

From the air quality standpoint, fossil fuel sources (such as coal, petroleum, and natural gas) are the main anthropogenic contributors to air pollution. While there was a negligible decrease of less than 10% in coal generation in 2020 compared to 2019, natural gas and petroleum generation resulted in significant increases of 16.5% and more than 14 times increase, respectively in 2020 compared to 2019 (Table S11). On the other hand, natural gas and petroleum were relatively unchanged during the Pre-lockdown period in 2020 compared to 2019 (Table S11). Similar increases in power generation due to residential usage were reported in the US and Europe and were associated with the pandemic lockdowns (Le Quéré et al., 2020).

There is a cluster of these fossil fuels-based power plants in central and southern Florida, which might explain the reason behind our previous observation of elevated SO_2 concentrations in central and southern Florida in comparison to northern Florida during the Lockdown period and the higher $PM_{2.5}$ concentrations observed in northern Florida when impacted by transport from central and southern Florida.

3.2.3. *Reduction in vehicular emissions*

The change in transportation due to the lockdown associated with the COVID-19 pandemic was examined in four cities where the daily available Apple mobility data was compared to a baseline on January 13th, 2020 (this day was chosen since it was the first infection case confirmed outside of China). According to Apple, the relative volume has increased since January 13th in several cities worldwide, consistent with normal, seasonal usage of Apple Maps (Apple Mobility Trends Reports, 2020). Summary statistics of the Apple mobility data are shown in Table S12. Although this data is associated with uncertainty, this analysis is not meant to be strictly quantitative, but the goal is to rather determine the change in mobility trends during the lockdown.

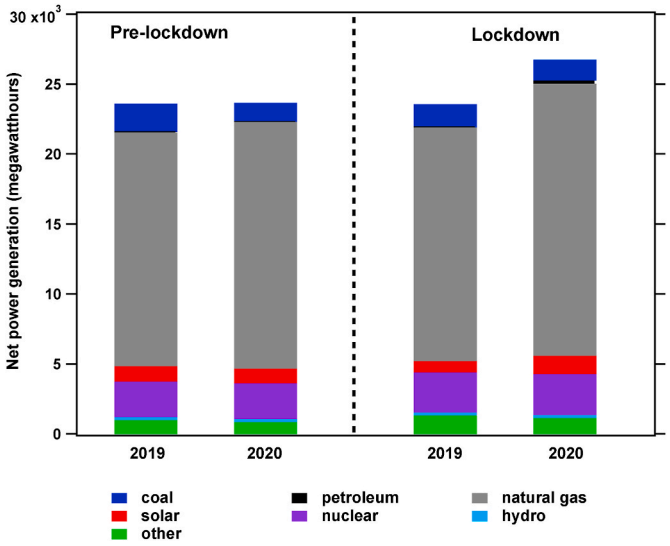

Fig. 3. A comparison of net power generation in Florida in 2019 and 2020 from various energy sources for Pre-lockdown: mid-February to mid-March, and Lockdown: mid-March to mid-April. Data based on https://www.eia.gov/opendata/qb.php?category=3390109.

As shown in Fig. 4, three categories of mobility data were examined, namely: private car "driving", public transportation "transit", and "walking". Amongst the three categories, the largest decrease was observed in the transit category at the investigated cities. Substantial decreases in transit use were observed in Orlando and Miami (>65 ± 10% decrease across days, ±1σ, where σ is the standard deviation of the percent change across days), the decrease was 63.9 ± 9.8% in Tampa, while in Jacksonville the decrease in transit corresponded to 46.9 ± 12.9%. This is an expected observation, since Miami, Orlando, and Tampa are highly populated urban cities with a wider transit system than cities located in the north of Florida. Both walking and driving decreased in all cities. On average, this decrease was comparable in Orlando, Miami, and Tampa and accounted for more than 50% ± 10%; however, Jacksonville exhibited a 35.5 ± 12.2% decrease in driving compared to a 28.3 ± 13.4% decrease in walking.

These traffic observations are in agreement with our air quality data that shows the highest decreases in NO_2 and CO concentrations in central and southern Florida. NO_2 is a major anthropogenic pollutant which is mainly produced from vehicular emissions. Parr et al. (2020) have reported a total reduction of almost 45% in traffic in 2020 from mid-March till mid-April compared to traffic data in 2019 during the same period in Florida. These reductions were more pronounced in urban areas compared to rural areas of the state (Parr et al., 2020). Consequently, reductions in NO_2 concentrations as a result of vehicular emissions during the lockdown period are predictable due to restricted mobility imposed by the state and local government. While Jacksonville displayed a decrease in the concentrations of these urban pollutants due to the lockdowns associated with the pandemic; however, the reduction was not as high as in other cities. It is to be noted that Jacksonville is a key city lying on I-95 highway which connects the northeastern of the US, especially New York and New Jersey to Florida. Given that many were moving to Florida through Jacksonville to avoid the northern hot spots of the pandemic, this may partially explain the less pronounced mobility reductions in Jacksonville than elsewhere in the state. This is also consistent with the fact that the central and northern regions of Florida were not completely closed during the lockdown opposed to a complete shutdown in the southern epicenter (Glanz et al., 2020).

4. Limitations and future directions

We have used the averaging process of data at all sites - including urban, suburban, and rural - available at each of the investigated metropolitan areas to gain a better insight into the variability of the levels of pollutants in each city. However, it should be noted that in some cases and for some pollutants, the data is limited to one or two sampling stations per city, as shown in Tables (S1–S6). This poses a limitation in this study as it might affect the magnitude of the concentrations of pollutants reported herein as well as their variability at a given city.

Air pollution contributes strongly to human mortality and morbidity including heart attacks, respiratory diseases, and others (Cohen et al., 2015). Improvements in air quality are anticipated to have a positive impact on human health. Hence, this work has implications on human health effects in Florida. More recently, literature shows that there is a correlation between air quality and the number of people infected by COVID-19; the number increased in environments with poor air quality conditions (Contini et al., 2020; Fattorini et al., 2020). Similar correlations were reported between mortality rates due to the virus and exposure to air pollution (Son et al., 2020). Further, the potential role of exposure to NO_2 and COVID-19 fatality has been previously reported (Ogen, 2020). The results herein suggest that control of vehicular emissions and the generation of more sustainable energy have the potential to improve air quality in Florida which could have significant impacts on both acute and chronic health outcomes. Future work should investigate whether the reductions in pollutant concentrations shown here were associated with improvements in public health. Previous

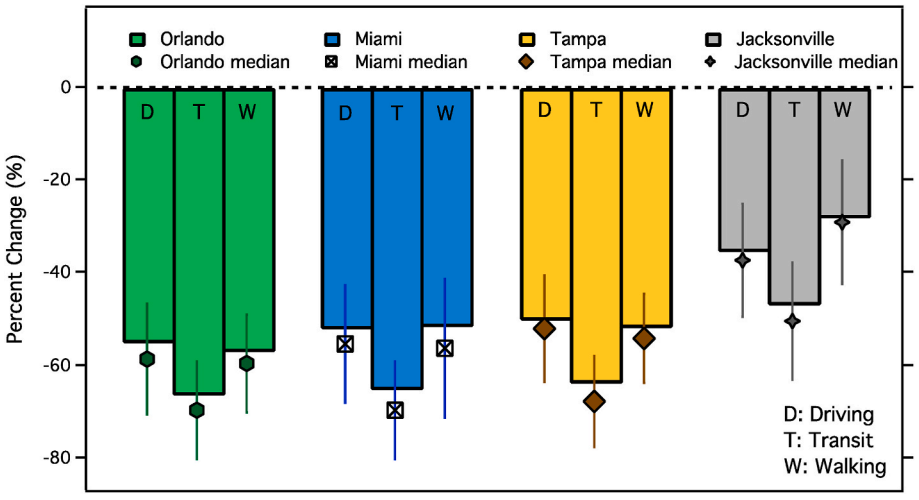

Fig. 4. Daily average percent change in driving, transit, and walking for Jacksonville, Orlando, Tampa, and Miami during the Lockdown period in 2020. No data was available for Tallahassee and Gainesville. Apple mobility data during the lockdown is compared to a baseline volume on January 13th, 2020 (Apple Mobility Trends Reports, 2020). Markers represent the median percent change values of the datasets for each city and the lines represent the standard deviation of these datasets across days.

studies have shown that even short-term reductions in pollution, for example during the Beijing Olympic Games (Rich et al., 2012), were associated with improvements in subclinical biomarker measures of cardiovascular health even among healthy, young adults. Moreover, longer-term improvements in air quality from a 13-month shutdown of a steel mill in Utah (Pope, 2010) was associated with a statistically significant reduction in respiratory hospitalizations.

5. Conclusions

This work took advantage of the natural experiment occurring due to the lockdown enforced by governments as a result of the COVID-19 pandemic to better understand the impact of anthropogenic pollutants on air pollution in Florida through a spatial distribution of atmospheric pollutants across the state. Overall, we have shown that a statistically significant decrease was observed for many of the atmospheric pollutants across the state during the lockdown associated with the pandemic in 2020. Our results highlight the necessity for high spatial resolution ground-level studies to capture the differences in behavior of atmospheric pollutants. These spatial effects would not have been manifested if the entire state was collectively studied, as was the case in previously reported studies (Shakoor et al., 2020). Our work has shown that for some pollutants such as NO_2 and CO, regulations of vehicular emissions can result in lowered levels of these pollutants. Unlike observations in other cities, restrictions in NO_x resulted in decreases in ozone levels in Florida since the environment is likely to be NO_x-limited. These observations indicate that promoting policies that restrict vehicular emissions in Florida would strongly improve the state's air quality. Changes in SO_2 concentrations are driven by power generation, highlighting the need for more sustainable energy sources for power generation in Florida. Based on results presented herein, the projected reductions in NO_2 and SO_2 will likely impact levels of not only NO_2 and SO_2, but perhaps $PM_{2.5}$ in the state (Pye et al., 2009). However, future laboratory and modeling studies are required to assess this effect.

Credit author statement

Marwa M.H. El-Sayed, Conceptualization, Methodology, Data curation, Formal analysis, Investigation, Resources; Software; Visualization, Validation, Writing – original draft, review & editing. Yasin F Elshorbany, Conceptualization, Formal analysis, Investigation, Writing – review & editing. Kirsten Koehler, Writing – review & editing.

Declaration of competing interest

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

Acknowledgements

The authors would like to thank the US EPA and FAWN for having their data available to the public. The authors would like to acknowledge financial support from Embry-Riddle Aeronautical University (ERAU), the USF COVID-19 Rapid Response Research Grant Award #100431, and the NSF AGS Award #1900795. This publication was developed, in part, under Assistance Agreement No. RD835871 awarded by the U.S. Environmental Protection Agency to Yale University. It has not been formally reviewed by EPA. The views expressed in this document are solely those of the authors and do not necessarily reflect those of the Agency.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.envpol.2021.117451.

References

Achakulwisut, P., Brauer, M., Hystad, P., Anenberg, S.C., 2019. Global, national, and urban burdens of paediatric asthma incidence attributable to ambient NO_2 pollution: estimates from global datasets. The Lancet Planetary Health 3 (4), e166–e178.

American Lung Association, 2020, (Accessed 30th March 2021), https://www.lung.org/.

Bekbulat, B., Apte, J.S., Millet, D.B., Robinson, A., Wells, K.C., Marshall, J.D., 2020. $PM_{2.5}$ and ozone air pollution levels have not dropped consistently across the US following societal covid response. ChemRxiv. https://doi.org/10.26434/chemrxiv.12275603.v7, 12275603, v2.

Berman, J.D., Ebisu, K., 2020. Changes in US air pollution during the COVID-19 pandemic. Sci. Total Environ. 739, 139864.

Burnett, R., Chen, H., Szyszkowicz, M., Fann, N., Hubbell, B., Pope, C.A., Spadaro, J.V., 2018. Global estimates of mortality associated with long-term exposure to outdoor fine particulate matter. Proc. Natl. Acad. Sci. Unit. States Am. 115 (38), 9592–9597.

IEA, 2020 US Electric System Operating Data, Accessed 15th July 2020; https://www.eia.gov/realtime_grid/.

Apple Mobility Trends Reports, 2020 (Apple, Accessed 30th July, 2020); https://www.apple.com/covid19/mobility/.

Cal Fire, 2020, (Accessed 30th March, 2021) https://climatediscovery.org/.

Carslaw, D.C., Beevers, S.D., Ropkins, K., Bell, M.C., 2006. Detecting and quantifying aircraft and other on-airport contributions to ambient nitrogen oxides in the vicinity of a large international airport. Atmos. Environ. 40 (28), 5424–5434. https://doi.org/10.1016/j.atmosenv.2006.04.062.

Carslaw, D.C., Ropkins, K., 2012. "Openair—an R package for air quality data analysis". Environ. Model. Software 27, 52–61. https://doi.org/10.1016/j.envsoft.2011.09.008.

Carslaw, D.C., Beevers, S.D., 2013. Characterizing and understanding emission sources using bivariate polar plots and k-means clustering. Environ. Model. Software 40, 325–329. https://doi.org/10.1016/j.envsoft.2012.09.005.

Cazorla, M., Herrera, E., Palomeque, E., Saud, N., 2020. What the COVID-19 lockdown revealed about photochemistry and ozone production in Quito, Ecuador. Atmos. Pollut. Res. https://doi.org/10.1016/j.apr.2020.08.028.

Chauhan, A., Singh, R.P., 2020. Decline in $PM_{2.5}$ concentrations over major cities around the world associated with COVID-19. Environ. Res. 187, 109634.

Chen, L.W.A., Chien, L.C., Li, Y., Lin, G., 2020. Nonuniform impacts of COVID-19 lockdown on air quality over the United States. Sci. Total Environ. 745 https://doi.org/10.1016/j.scitotenv.2020.141105, 141105.

Cohen, A.J., Brauer, M., Burnett, R., Anderson, H.R., Frostad, J., Estep, K., Balakrishnan, K., Brunekreef, B., Dandona, L., Dandona, R., Feigin, V., Freedman, G., Hubbell, B., Jobling, A., Kan, H., Knibbs, L., Liu, Y., Martin, R., Morawska, L., Pope, C.A., Shin, H., Straif, K., Shaddick, G., Thomas, M., van Dingenen, R., van Donkelaar, A., Vos, T., Murray, C.J.L., Forouzanfar, M.H., 2015. Estimates and 25-year trends of the global burden of disease attributable to ambient air pollution: an analysis of data from the Global Burden of Diseases Study. Lancet 1907–1918, 2017; 389(10082)PMID: WOS:000400973500026.

Collivignarelli, M.C., Abbà, A., Bertanza, G., Pedrazzani, R., Ricciardi, P., Carnevale Miino, M., 2020. Lockdown for COVID-2019 in Milan: what are the effects on air quality? Sci. Total Environ. 732, 139280.

Contini, D., Costabile, F., 2020. Does air pollution influence COVID-19 outbreaks? Atmosphere 11 (4).

Dantas, G., Siciliano, B., França, B.B., da Silva, C.M., Arbilla, G., 2020. The impact of COVID-19 partial lockdown on the air quality of the city of Rio de Janeiro, Brazil. Sci. Total Environ. 729, 139085.

Delfino, R.J., Staimer, N., Tjoa, T., Gillen, D.L., Schauer, J.J., Shafer, M.M., 2013. Airway inflammation and oxidative potential of air pollutant particles in a pediatric asthma panel. J. Expo. Sci. Environ. Epidemiol. 23 (5), 466–473. https://doi.org/10.1038/jes.2013.25.

Elshorbany, Y.F., Kleffmann, J., Kurtenbach, R., Rubio, R., Lissi, E., Villena, G., Rickard, A.R., Pilling, M.J., Wiesen, P., 2009b. Summertime Photochemical Ozone Formation in Santiago de Chile. Atmos. Environ. 43, 6398–6420.

Elshorbany, Y.F., Kurtenbach, R., Wiesen, P., Lissi, E., Rubio, M., Villena, G., Gramsch, E., Rickard, A.R., Pilling, M.J., Kleffmann, J., 2009a. Oxidation capacity of the city air of Santiago, Chile. Atmos. Chem. Phys. 9, 2257–2273.

Elshorbany, Y.F., Kapper, H.C., Ziemke, J.R., Parr, S.A., 2021. "The status of air quality in the United States during the COVID-19 pandemic: a remote sensing perspective". Rem. Sens. 13, 369. https://doi.org/10.3390/rs13030369, 2021.

EPA, https://www.epa.gov/newsreleases/all-areas-florida-now-attainment-sulfur-dioxide, 2020. Last visited: October 30, 2020.

Esworthy, R., McCarthy, J.E., 2013. The National Ambient Air Quality Standards (NAAQS) for Particulate Matter (PM): EPA's 2006 Revisions and Associated Issues. Library of Congress, Congressional Research Service.

Fattorini, D., Regoli, F., 2020. Role of the chronic air pollution levels in the Covid-19 outbreak risk in Italy. Environ. Pollut. 264, 114732.

Glanz, J., B. Carey, J. Holder, D. Watkins, J. Valentino-DeVries, R. Jojas, and Leatherby, L.: "Where America didn't stay home even as the virus spread." Accessed April 2, 2020. https://www.nytimes.com/interactive/2020/04/02/us/coronavirus-social-distancing.html.

Hoang, A.T., Huynh, T.T., Nguyen, X.P., Nguyen, T.K.T., Le, T.H., 2021. An analysis and review on the global NO2 emission during lockdowns in COVID-19 period", Energy Sources, Part A: Recovery. Utilization, and Environmental Effects 1–21. https://doi.org/10.1080/15567036.2021.1902431.

Holloway, T., Fiore, A., Hastings, M.G., 2003. Intercontinental Transport of Air Pollution: will emerging science lead to a new hemispheric treaty? Environ. Sci. Technol. 37 (20), 4535–4542. https://doi.org/10.1021/es034031g.

Jechow, A., Hölker, F., 2020. Evidence that reduced air and road traffic decreased artificial night-time skyglow during COVID-19 lockdown in berlin, Germany. Rem. Sens. 12 (20), 3412. https://doi.org/10.3390/rs12203412.

Karaer, A., Balafkan, N., Gazzea, M., Arghandeh, R., Ozguven, E.E., 2020. Analyzing COVID-19 impacts on vehicle travels and daily nitrogen dioxide (NO_2) levels among Florida counties. Energies 13, 6044. https://doi.org/10.3390/en13226044.

Kerimray, A., Baimatova, N., Ibragimova, O.P., Bukenov, B., Kenessov, B., Plotitsyn, P., Karaca, F., 2020. Assessing air quality changes in large cities during COVID-19 lockdowns: the impacts of traffic-free urban conditions in Almaty. Kazakhstan", Sci. Tot. Environ. 730, 139179.

Kroll, J.H., Heald, C.L., Cappa, C.D., Farmer, D.K., Fry, J.L., Murphy, J.G., Steiner, A.L., 2020. The complex chemical effects of COVID-19 shutdowns on air quality. Nat. Chem. 12 (9), 777–779.

Le, V.V., Huynh, T.T., Ölçer, A., Hoang, A.T., Le, A.T., Nayak, S.K., Pham, V.V., 2020. A remarkable review of the effect of lockdowns during COVID-19 pandemic on global PM emissions. Energy Sources, Part A Recovery, Util. Environ. Eff. 1–16. https://doi.org/10.1080/15567036.2020.1853854.

Le Quéré, C., Jackson, R.B., Jones, M.W., et al., 2020. Temporary reduction in daily global CO_2 emissions during the COVID-19 forced confinement. Nat. Clim. Change 10, 647–653. https://doi.org/10.1038/s41558-020-0797-x.

Lelieveld, J., Pozzer, A., Pöschl, U., Fnais, M., Haines, A., Münzel, T., 2020. Loss of life expectancy from air pollution compared to other risk factors: a worldwide perspective. Cardiovasc. Res. 116 (11), 1910–1917. https://doi.org/10.1093/cvr/cvaa073.

Li, L., Li, Q., Huang, L., Wang, Q., Zhu, A., Xu, J., Liu, Z., Li, H., Shi, L., Li, R., Azari, M., Wang, Y., Zhang, X., Liu, Z., Zhu, Y., Zhang, K., Xue, S., Ooi, M.C.G., Zhang, D., Chan, A., 2020. Air quality changes during the COVID-19 lockdown over the Yangtze River Delta Region: an insight into the impact of human activity pattern changes on air pollution variation. Sci. Total Environ. 732, 139282.

Lusher, W.R., Jackson, J.L., Morgan, K.T., 2008. The Florida automated weather network: ten years of providing weather information to Florida growers. Proc. Fla. State Hortic. Soc. 121, 69–74 (December).

Nakada, L.Y.K., Urban, R.C., 2020. COVID-19 pandemic: impacts on the air quality during the partial lockdown in São Paulo state, Brazil. Sci. Total Environ. 730, 139087.

Niroumand-Jadidi, M., Bovolo, F., Bruzzone, L., Gege, P., 2020. Physics-based bathymetry and water quality retrieval using planetscope imagery: impacts of 2020 Covid-19 lockdown and 2019 extreme flood in the Venice Lagoon. Rem. Sens. 12 (15), 2381.

Nguyen, X.P., Hoang, A.T., Ölçer, A.I., Huynh, T.T., 2021. Record decline in global CO_2 emissions prompted by COVID-19 pandemic and its implications on future climate change policies. Energy Sources, Part A Recovery, Util. Environ. Eff. 1–4.

Ogen, Y., 2020. Assessing nitrogen dioxide (NO_2) levels as a contributing factor to coronavirus (COVID-19) fatality. Sci. Total Environ. 726, 138605.

Parr, S., Wolshon, B., Renne, J., Murray-Tuite, P., Kim, K., 2020. Traffic impacts of the COVID-19 pandemic: statewide analysis of social separation and activity restriction. Nat. Hazards Rev. 21 (3), 04020025. DOI: 10.1061/(ASCE)NH.1527- 6996.0000409.

Pope III, C.A., 1991. Respiratory hospital admissions associated with PM10 pollution in Utah, salt lake, and cache valleys. Arch. Environ. Health 46 (2), 90–97. https://doi.org/10.1080/00039896.1991.9937434.

Pye, H.O.T., Liao, H., Wu, S., Mickley, L.J., Jacob, D.J., Henze, D.K., Seinfeld, J.H., 2009. "Effect of changes in climate and emissions on future sulfate-nitrate-ammonium aerosol levels in the United States". J. Geophys. Res.: Atmosphere 114 (D1). https://doi.org/10.1029/2008JD010701.

Rich, D.Q., Kipen, H.M., Huang, W., Wang, G., Wang, Y., Zhu, P., et al., 2012. Association between changes in air pollution levels during the Beijing Olympics and biomarkers of inflammation and thrombosis in healthy young adults. J. Am. Med. Assoc. 307 (19), 2068–2078. https://doi.org/10.1001/jama.2012.3488.

Sanap, S.D., 2021. Global and regional variations in aerosol loading during COVID-19 imposed lockdown. Atmos. Environ. 246, 118132. https://doi.org/10.1016/j.atmosenv.2020.118132.

Shakoor, A., Chen, X., Farooq, T.H., et al., 2020. Fluctuations in environmental pollutants and air quality during the lockdown in the USA and China: two sides of COVID-19 pandemic. Air Qual. Atmos. Health 13, 1335–1342. https://doi.org/10.1007/s11869-020-00888-6.

Sharma, S., Zhang, M., Gao, J., Zhang, H., Kota, S.H., 2020. Effect of restricted emissions during COVID-19 on air quality in India. Sci. Total Environ. 728, 138878.

Sicard, P., De Marco, A., Agathokleous, E., Feng, Z., Xu, X., Paoletti, E., Rodriguez, J.J.D., Calatayud, V., 2020. Amplified ozone pollution in cities during the COVID-19 lockdown. Sci. Total Environ. 735, 139542.

Son, J.Y., Fong, K.C., Heo, S., Kim, H., Lim, C.C., Bell, M.L., 2020. Reductions in mortality resulting from reduced air pollution levels due to COVID-19 mitigation measures. Sci. Total Environ. 744, 141012.

Tanzer-Gruener, R., Li, J., Eilenberg, S.R., Robinson, A.L., Presto, A.A., 2020. Impacts of modifiable factors on ambient air pollution: a case study of COVID-19 shutdowns. Environ. Sci. Technol. Lett. 7 (8), 554–559. https://doi.org/10.1021/acs.estlett.0c00365.

Tobías, A., Carnerero, C., Reche, C., Massagué, J., Via, M., Minguillón, M.C., Alastuey, A., Querol, X., 2020. Changes in air quality during the lockdown in Barcelona (Spain) one month into the SARS-CoV-2 epidemic. Sci. Total Environ. 726, 138540.

US Census Bureau, 2019. https://www.census.gov/quickfacts/fact/table/FL/POP060210. (Accessed 1 May 2020).

Ventera, Z.S., Aunan, K., Chowdhury, S., Lelieveld, J., 2020. COVID-19 lockdowns cause global air pollution declines. Proc. Natl. Acad. Sci. Unit. States Am. 117 (32), 18984–18990. https://doi.org/10.1073/pnas.2006853117.

WHO (World Health Organization), 2016. Ambient Air Pollution: A Global Assessment of Exposure and Burden of Disease.

WHO (World Health Organization), 2020. WHO director-General's opening remarks at the media briefing on COVID19 - 11 March 2020. https://www.who.int/dg/speeches/detail/who-director-general-s-opening-remarks-at-the-media-briefing-on-covid-19—11-march-2020. (Accessed 21 April 2020).

WHO, 2021. Weekly epidemiological update. Accessed 26th Feb 2021. https://www.who.int/publications/m/item/weekly-epidemiological-update—23-february-2021. (Accessed 23 February 2021).

Zangari, S., Hill, D.T., Charette, A.T., Mirowsky, J.E., 2020. Air quality changes in New York City during the COVID-19 pandemic. Sci. Total Environ. 742, 140496.

Zheng, B., Geng, G., Ciais, P., Davis, S.J., Martin, R.V., Meng, J., et al., 2020. "Satellite-based estimates of decline and rebound in China's CO_2 emissions during COVID-19 pandemic". Science Advances 6 (49). https://doi.org/10.1126/sciadv.abd4998 eabd4998.

Zhu, H., Wei, L., Niu, P., 2020. The novel coronavirus outbreak in Wuhan, China. Glob. Health Res. Policy. https://doi.org/10.1186/s41256-020-00135-6, 5, 6.