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The Breathing Human Infrastructure: Integrating Air Quality, Traffic, And Social Media Indicators

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The breathing human infrastructure: Integrating air quality, traffic, and social media indicators

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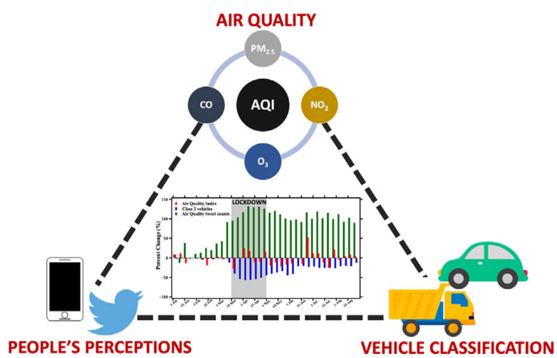
HIGHLIGHTS

- Atmospheric pollutants exhibited significant changes during the lockdown in Florida.
- Decreases in traffic were observed for all vehicle classes but were most profound among passenger cars.
- Increases in air quality-related Tweets were observed immediately after the start and end of the lockdown.
- Strong correlations were observed between Tweets, traffic, and NO2 levels after the lockdown.
- People's perceptions correlated with traffic and its main atmospheric pollutants but not with AQI.

GRAPHICAL ABSTRACT



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ABSTRACT

Outdoor air pollution is a complex system that is responsible for the deaths of millions of people annually, yet the integration of interdisciplinary data necessary to assess air quality's multiple metrics is still lacking. This case study integrates atmospheric indicators (concentrations of criteria pollutants including particulate matter and gaseous pollutants), traffic indicators (permanent traffic monitoring station data), and social indicators (community responses in Twitter archives) representing the interplay of the three critical pillars of the United Nations' Triple Bottom Line: environment, economy, and society. During the watershed moment of the COVID-19 pandemic lockdowns in Florida, urban centers demonstrated the gaps and opportunities for understanding the relationships, through correlations rather than causations, between urban air quality, traffic emissions, and public perceptions. The relationship between the perception and the traffic variables were strongly correlated, however no correlation was observed between the perception and actual air quality indicators, except for NO_2. These observations might consequently infer that traffic serves as people's proxy for air quality, regardless of actual air quality, suggesting that social media messaging around asthma may be a way to monitor traffic patterns in areas where no infrastructure currently exists or is prohibited to build. It also indicates that people are less likely to be reliable sensors to accurately measure air quality due to bias in their observations of traffic volume and/or confirmation biases in broader social discourse. Results presented herein are of significance in demonstrating the capacity for interdisciplinary studies to consider the predictive capacities of social media and air pollution, its use as both lever and indicator of public support for air quality legislation and clean-air transitions, and its ability to overcome limitations of surface monitoring stations.

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1. Introduction

Air pollution is a complex socio-environmental system with significant economic implications, drawing all three dimensions of the United Nations Sustainable Development Goals summarized in the triple bottom line. Anthropogenic pollutant emissions from industry and transportation adversely impact human health as well as climate change causing tremendous economic challenges. The World Health Organization (WHO) estimates six to seven million deaths annually due to exposure to outdoor air pollution (WHO, 2014). Urban communities located near major roadways and industrial centers consistently experience higher air pollutant concentrations than their suburban counterparts (Filigrana et al., 2020). The residents of these communities are also more likely to experience emphysema, chronic obstructive pulmonary diseases (COPD), cancer, and cardiac disease (Lv et al., 2020; Williams et al., 2009). In the US, these communities are more likely to be significantly poorer and populated by racial minorities (Miranda et al., 2011; Bell and Ebisu, 2012; Bravo et al., 2016; Reames and Bravo, 2019). The United Nations Sustainable Development Goals, including the Climate Action, set for 2030 rest on three pillars balancing planet, prosperity, and people–incorporating the environmental, economic, and social perspectives of sustainability, respectively. Understanding the relationship between air pollutants, vehicle emissions, and how urban communities perceive air quality is an important step toward understanding this dynamic system.

Several studies have explored the link between air quality and traffic especially during the COVID-19 pandemic (e.g., Chen et al., 2021; Gualtieri et al., 2020; Parker et al., 2020). Others have focused on associations between air quality and society (e.g., Pramanik et al., 2020; Zhai and Cheng, 2020). However, to the best of our knowledge, no other study has attempted to characterize the three indicators presented in this paper. This paper analyzes traffic emissions, urban air quality, and public perception of respiratory quality measured in a natural empirical manner, in situ, during the onset of the COVID-19 pandemic. In response, the WHO, U.S. Center for Disease Control (CDC), and governing bodies issued directives to eliminate non-essential travel. In the US, government restrictions and actions varied between states, however, most state and local governments closed restaurants, schools, retail stores, and offices in an effort to promote social distancing. The COVID-19 pandemic lockdowns had profound impacts on travel patterns which were assumed to be reflected in urban air quality and posited to be perceptible to urban populations. This paper uses urban Florida as a case study to demonstrate the relationship between three unique air pollutant indicators: ground atmospheric pollutant concentrations, roadway traffic counts, and the perception of air quality extracted from Twitter comparing historical data with the months spanning the lockdown (January–September) of 2020. Florida was chosen due to its population and economic growth in comparison to other states in the US in addition to its diversity in atmospheric pollutant sources and meteorological patterns.

Vehicular emissions are linked to the subsequent elevated concentrations of four pernicious atmospheric pollutants referred to by the US EPA as criteria pollutants regulated through the National Ambient Air Quality Standards (NAAQS). Particulate matter, CO, NO_2, and ozone are among these regulated pollutants. As such, these pollutants are closely monitored in 4000 sites across the U.S. (EPA, 2022) under the umbrella of the U.S. Environmental Agency (U.S. EPA), and in 41 sites across Florida (FLDEP, 2022) operated by the Florida Department of Environmental Protection (FLDEP). The Air Quality Index (AQI) is a normalized metric calculated based on ground level air pollutant concentration measurements (U.S. EPA, 2018). Critically, a change in these pollutants was reported in cities worldwide concurrently with the COVID-19 lockdowns. This included a constant decrease in NO_2 concentrations in China, Italy, Germany, India, and the U.S. (Xing et al., 2020; Collivignarelli et al., 2020; Selvam et al., 2020; Zangari et al., 2020; Bauwens et al., 2020; Goldberg et al., 2020; Naeger and Murphy, 2020; Tanzer-Gruener et al., 2020) and was attributed to the reduction in traffic loads during the extended lockdown periods. Surprisingly, this trend was not observed for ozone and $PM_{2.5}$ levels. For instance, ozone concentrations increased in VOC-limited environments (Xing et al., 2020; Salma et al., 2020), but decreased in NO_x-limited environments (El-Sayed et al., 2021). Erratically, $PM_{2.5}$ levels increased in some locations such as in north China (Xing et al., 2020), and decreased in cities such as New York (Zangari et al., 2020) and Wuhan (Sulaymon et al., 2021). By integrating evidence from traffic patterns, it provides some of the answers to these conflicting reports.

The COVID-19 pandemic with its associated social distancing requirements and economic closures resulted in a nearly universal change in traffic patterns (Benita, 2021). Sudden and drastic decreases in passenger vehicle travel as well as a general shift away from share modes were documented across the globe (Abdullah et al., 2021; Bartuska and Masek, 2021; Lee et al., 2020; König and Dreßler, 2021; Muley et al., 2021; Politis et al., 2021; Simunek et al., 2021; Zhang et al., 2021). Most of the reviewed studies relied upon survey data or vehicle/passenger count information. In general, the international literature suggests traffic decreases ranged from 33% to over 50%, depending on the timing, location, and data collection method. In the U.S., statewide analysis suggests that traffic decreases of over 50% were common by the end of March and into April (Doucette, 2021; Liu and Stern, 2021; Parr et al., 2020). A nationwide survey in the U.S. found that traffic decreased by 40% (Bradley et al., 2021), while an analysis of continuous count station data from ten states across the U.S. reported traffic decreases ranging from 55 to 69% in late March and early April (Parr et al., 2021). These traffic data were only partially acknowledged in changing social media discourse about the relationship between air quality and traffic patterns, demonstrating the scope of human perception to accurately identify the changing environmental pollutant causes.

While popularizing the connection between reduced air pollution and work from home has been an environmental goal since the 1970s (Van Lier et al., 2012; Irwin, 2004; Ursery, 2003), the COVID-19 stay-at-home orders presented a watershed moment for people to physically experience it first-hand (Belzunegui-Eraso and Erro-Garcés, 2020) while synchronously documenting and sharing their perceptions. Generally, those outside of the social sciences studying air quality and COVID-19 view social media as a tool for research dissemination or influencing safety precautions (Barcelo, 2020; Chan et al., 2020; Agarwal et al., 2021). But worldwide lockdowns gave the exceptional ability for the public to recognize improved air quality using their own body as an instrument. Mainstream media stories from around the locked-down world celebrated the "silver lining" of a "healing" earth that was only in part corroborated by science (Carrington, 2020; Biswas, 2020; Lal et al., 2020). Personal accounts on social media documented worldwide changes to embodied sensations of changing air quality. These accounts were visceral, often relying on basic senses like sight and smell, and captured the transfixed population's imagination with uncanny accounts of air improvement so realistic they felt like an "enchantment" or "dreamlike" state (Kesting, 2021; Ramasamy et al., 2020). The centrality of social media to affecting these environmental perceptions was only enhanced as mobility and other in-person social outlets were drastically reduced; personal posts remained a critical discourse medium.

Fig. 1 provides a broad overview of this paper's findings. Comparing similar weeks between 2020 and baseline conditions (i.e., 2019 data for traffic and air quality tweets, and 2015–2019 averages for air quality), the figure shows the percent change in AQI, passenger car vehicle counts (Federal Highway Administration Vehicle Classification 2), and in the number of tweets referencing air quality. This paper investigates the relationship between the traffic and air quality tweets to several other common pollutants associated with air quality. The paper then postulates several possible reasons for the disparity between the explanatory variables, before concluding with a discussion of the broader impacts of this work. Through the case study of urban areas of Florida as integrated system, we demonstrate the methodological and analytical challenges of integrating data across fields beyond issues of expanding the breadth and depth of existing datasets. During the pandemic, while Loia and Adinolfi (2021) demonstrate that people's sentiments linking telework and environmental awareness were not significantly changed, our study demonstrates a more direct

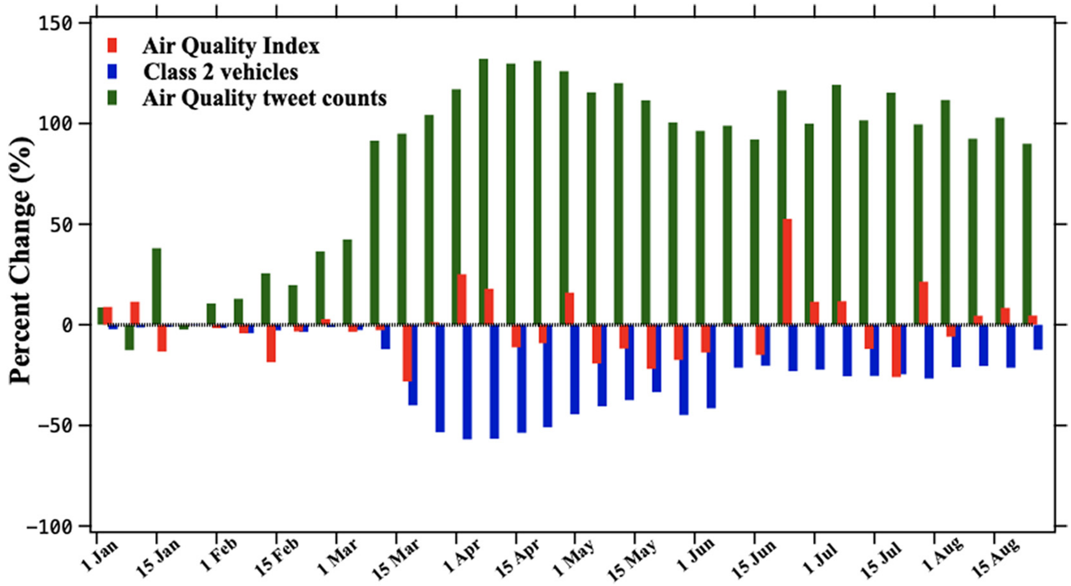

Fig. 1. A weekly percent change in 2020 from baseline levels among the constitution air quality indicators from 1st January–30th August.

relationship is evident when examining air quality discourse and traffic patterns. Our study is one of growing interdisciplinary studies that are just beginning to consider the predictive capacities of social media and air pollution (Zhai and Cheng, 2020), its use as both lever and indicator of public support for air quality legislation and clean-air transitions (Liang et al., 2021), and its ability to overcome limitations of surface monitoring stations (Shan et al., 2021).

2. Methodology

2.1. Ground based air quality measurements

Hourly pollutant data was collected in five urban cities in the state of Florida namely Jacksonville, Tallahassee, Orlando, Tampa, and Miami. The sites represent diverse locations in terms of their atmospheric sources as well as their meteorological conditions. Hourly $PM_{2.5}$, carbon monoxide (CO), ozone (O_3), and nitrogen dioxide (NO_2) measurements from these stations were acquired from the Florida Department of Environmental Protection (https://aqs.epa.gov/api) starting from January 1st till the end of August for six years (2015–2020). Precipitation data 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/). A linear mixed-effects (LME) model using MATLAB (MathWorks, Inc., Natick, MA, Version R2018A) was used to test the statistical significance of the changes in the daily average concentrations of atmospheric pollutants in 2020 compared to their corresponding baseline averages (2015–2019).

2.2. Traffic monitoring

The traffic monitoring sites report continuous hourly traffic counts (FHWA, 2014). The FHWA identifies 13 vehicle classifications or "classes". This study investigates the following four most pervasive vehicle classes in Florida (comprising over 95% of all observations):

- Class 2 - Passenger Cars
- Class 5 - Two Axle, Six Tire, Single Unit
- Class 8 - Three Axle, Single Unit
- Class 9 - Five Axle Tractor Semitrailer

Traffic data is provided by the Florida Department of Transportation (FDOT). The dataset includes hourly traffic counts, by vehicle classification for the period of January 1st - August 31st for both 2019 and 2020. The dataset consists of 54 continuous count stations located in the cities of Gainesville, Jacksonville, Miami, Orlando, and Tampa. Vehicle classification data was not available at any of the four continuous count stations located within the urban region of Tallahassee during the period of 2/29/2020 and July 30, 2020. Due to the lack of sufficient data, Tallahassee was excluded from the traffic analysis.

2.3. Public perception

Social media discourse data was collected via Twitter's version 1.1 Tweet search Application Programming Interface (API). The API was queried to collect Tweets containing the keywords, phrases, or hashtags "asthma", "air quality", "air pollution", and/or "clean air." It was limited to original Tweets in English that were sent between January 1st, 2015 and August 31st, 2020 and were geolocated in Florida. The geolocation criteria included location information attached to an individual Tweet or to the sending user's profile. A total of 5286 Tweets were collected based on these criteria. A qualitative content analysis was conducted and used inductive methods from grounded theory, phasing open coding, and axial coding to gain a general sense of the most relevant themes and subject terms in existing content patterns. The resulting codebook identified Tweets with specific mention of key subject terms: traffic, gridlock, rush hour, highway, freeway, road, street, car(s), truck(s), driver(s), delivery, rideshare (including names of popular companies), gas(oline), or parking. The Tweets identified by the codebook were randomized for date and all information beyond the Tweet was hidden for content analysis.

3. Results and discussion

3.1. Air pollutant indicator overview

To gain insight into the air quality during the lockdowns associated with the COVID-19 pandemic, the average hourly concentrations of each pollutant were calculated as the average value of all six cities under investigation. Specific pollutants were selected among other criteria pollutants because of their direct link to traffic (vehicular emissions such as NO_2 and CO), and to human perception (visibility and respiratory impairments such as NO_2, $PM_{2.5}$, and O_3). Hourly pollutant concentrations from January 1st, 2020–August 31st, 2020 were compared to their corresponding baseline defined as the five-year (2015–2019) average observations during the same time period. Concentrations of selected atmospheric pollutants in Florida are shown in Fig. S1. All analyses conducted throughout this study are based on dry periods (corresponding to more than 90% of the hourly data) with no rainfall to eliminate the impact of meteorological conditions on the results we report herein. We test the statistical significance of historical changes in concentrations using an LME model and the results of this test are shown in detail in Table S1.

Fig. 2 shows percent changes in monthly median concentrations of atmospheric pollutants in 2020 compared to their corresponding baseline averages. It could be deduced from Fig. 2 that there has not been a statistically significant change in median NO_2 concentrations in 2020 compared to the median value for the previous five years before the start of the lockdown period. However, a statistically significant decrease of 19.6% ± 5.6% (±1σ) was observed in the second half of March which lasted into April (17.4 ± 5%) (Fig. S1a). After the lockdown period, lower decreases in NO_2 concentrations were observed from May till the end of August, yet these decreases were still statistically significant according to the LME model. O_3 concentrations exhibited similar trends to those of NO_2. Concentrations of O_3 decreased in Florida in 2020 during the period of the lockdown compared to baseline averages by about 13.3 ± 2.7% across the state in the second half of March and in April (Figs. 2 and 1b). Statistically significant reductions in O_3 concentrations lasted after the lockdown period as shown in Fig. 2. These similar behavior patterns of NO_2 and O_3 infer that ozone formation in Florida is sensitive to NO_2 concentrations in accord to results reported in El-Sayed et al. (2021). CO levels did not exhibit the same trends as neither NO_2 nor O_3 concentrations, except for a statistically significant decrease in the second half of March of approximately 14.2 ± 6%, (Fig. 2 and S1d), but this change did not continue beyond the month of March. The pattern in CO concentrations after the end of the lockdown did not show any consistent trend. This is possibly owing to sources other than vehicular emissions contributing to CO emissions in Florida. El-Sayed et al. (2021) reported increases in power generation during the lockdown which might explain the enhancement in CO levels in April. As for $PM_{2.5}$ concentrations, these did not show any statistically significant change prior to mid-March. Conversely, in the second half of March, a slight decrease in the median of $PM_{2.5}$ levels of 6.0 ± 4.5% was observed in Florida in 2020 compared to baseline averages during the same period. On the other hand, a pronounced increase of ~15 ± 4.3% was observed in concentrations of $PM_{2.5}$ in April. A statistically significant decrease of −6.0 ± 7.9% was observed in fine-particle concentrations until the end of July.

Improvements in air quality during the lockdowns were reported in several cities around the globe primarily due to the reduction in traffic (Chen et al., 2021; Jephcote et al., 2021; Chen et al., 2020). However, not all pollutants demonstrated a consistent decreasing trend during the COVID-19 lockdown. While eductions in NO_2 (e.g., Karaer et al., 2020, El-Sayed et al., 2021), CO (e.g., Chen et al., 2020), and $PM_{2.5}$ concentrations (e.g., Rodríguez-Urrego and Rodríguez-Urrego, 2020) were observed in major cities around the globe, however, O_3 concentrations did not manifest a consistent trend due to its complex dependence on NO_x-VOC chemistry (e.g., Parker et al., 2020; Collivignarelli et al., 2020).

3.2. Traffic indicator overview

The percent change in traffic in 2020 compared to 2019 is presented in Fig. 3 for the four vehicle classifications under investigation. In general, the level and duration of decreases in traffic appear heavily dependent upon vehicle class. Significant traffic decreases did not occur until after the governor's emergency declaration on March 9, 2020 (Parr et al., 2020). The month of March is, therefore, subdivided in the figure as *Mar I* (March 1st–March 15th) and *Mar II* (March 16th - March 31st). Fig. 3 shows that traffic between January 2020 and the first half of March was nominally different from traffic during the same period in 2019, regardless of vehicle class. Decreases in traffic were emphasized for Class 2 vehicles, i.e., passenger cars. For example, the second half of March 2020 experienced a nearly 43%

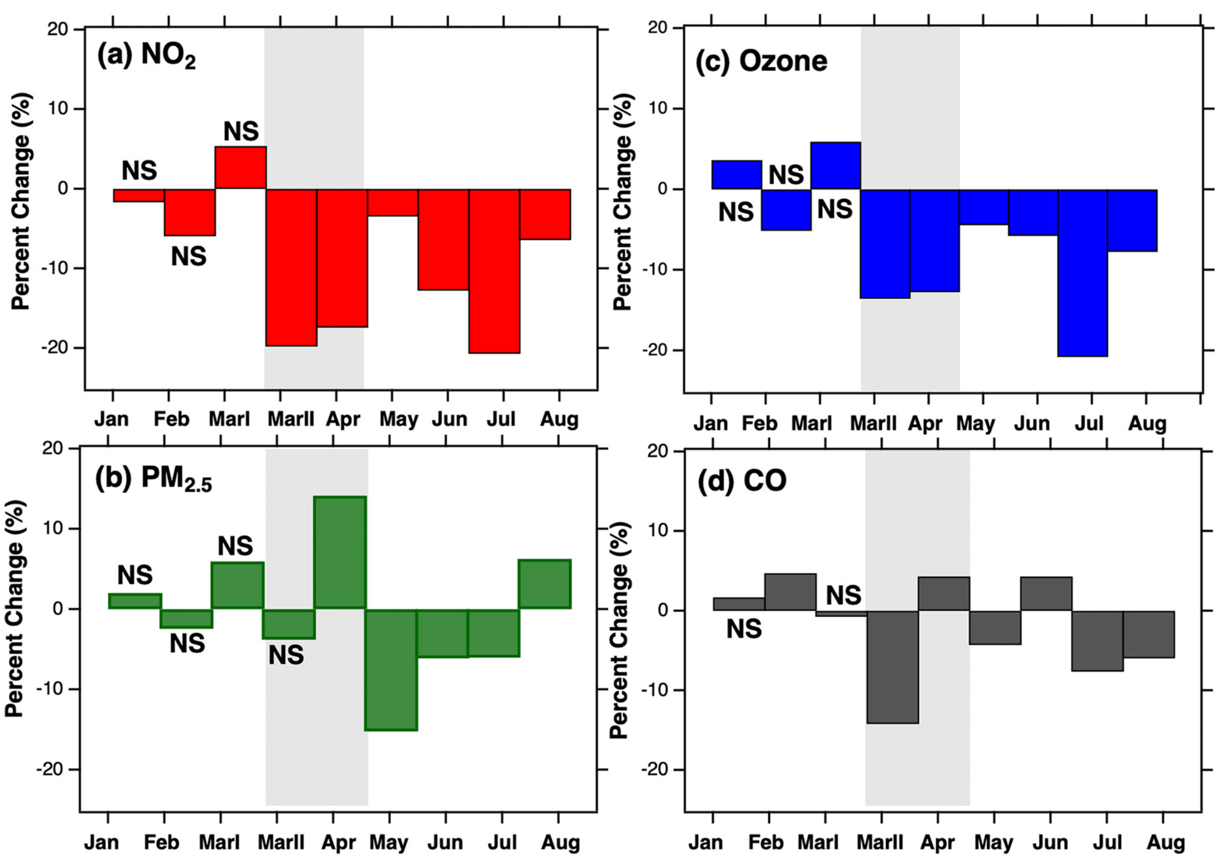

Fig. 2. Monthly percent change in median pollutant concentrations from January 1st–August 30th. March is divided into Mar I and Mar II corresponding to 1st - 15th March, and 16th–31st March, respectively. Gray shaded area represents the period of complete lockdown (15th March–30th April). NS refers to months where no statistical significance was reported for the median concentrations of the pollutant against historic averages.

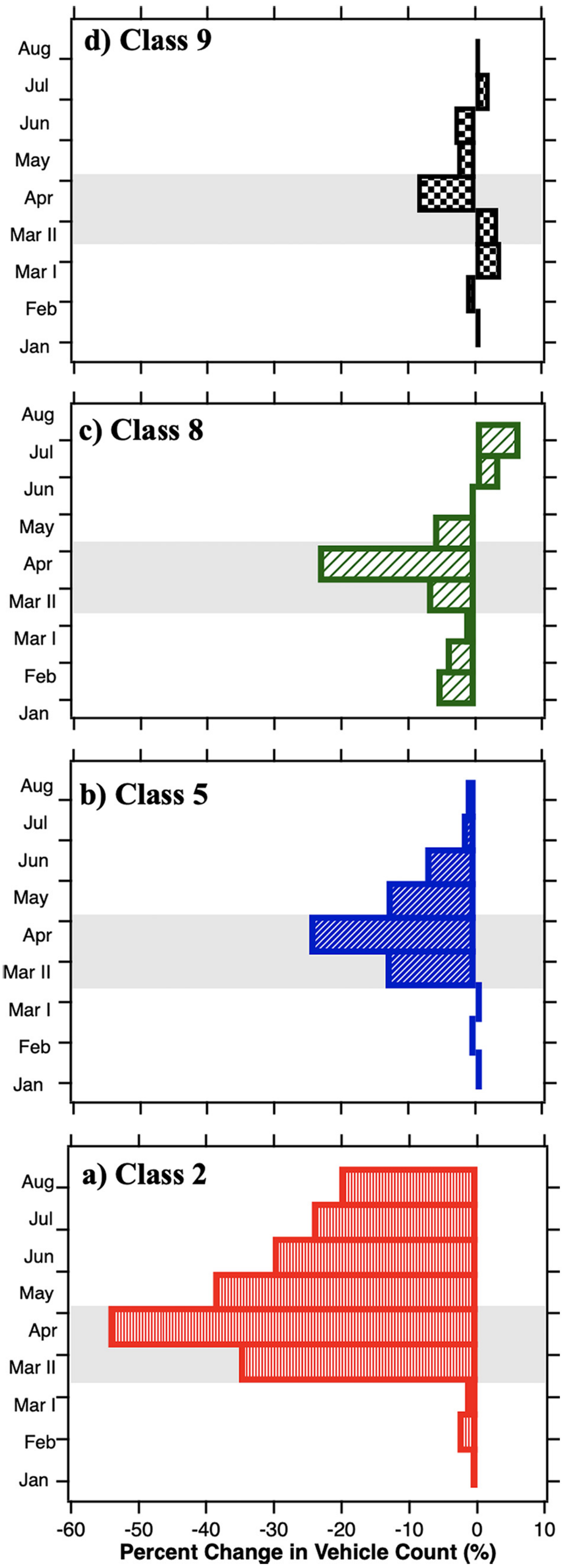

Fig. 3. Percent change in monthly traffic volume by vehicle classification for (a) Class 2, (b) Class 5, (c) Class 8, and (d) Class 9 vehicles in 2020 compared to 2019. Gray shaded area represents the period of complete lockdown (15th March–30th April).

decrease in Class 2 vehicles compared to 2019, whereas reductions were 12% and 6%, for Classes 5 and 8 vehicles, respectively. Furthermore, Class 9 vehicles nominally increased to 8% during this same period. The largest decrease of vehicles was observed in April, regardless of vehicle class. Class 2 vehicles were reduced by 54%, Classes 5 and 8 vehicles deacresed by approximately 24%, and Class 9 vehicles decreased by more than 8%. In the beginning of May 2020, traffic began to return to its normal conditions similar to those conditions prior to the lockdown. While the number of Classes 2 and 5 vehicles were lower than their values in 2019 by 37 and 14%, respectively, Classes 8 and 9 vehicles exhibited minor reductions of 7% and 5%, respectively. By June, Class 2 vehicle traffic appeared to stabilize around a 20% reduction, while larger vehicle classes had nearly returned to pre-pandemic levels. The months of July and August were a continuation of the trend which began in June. The number of Class 2 vehicles decreased by approximately 20% in June whereas the larger classes were operating at or above their 2019 benchmark.

To test for significance, traffic within each vehicle class was compared using a paired, two-sided *t*-test. The analysis was carried out by investigating daily traffic totals for similar days between years. In total, 976 t-test were conducted, one for each day between January 1st and August 31st, for each of the four vehicle classes ($244 \times 4 = 976$). Prior to conducting the *t*-test, traffic was evaluated for normality using the Shapiro-Wilk test (Table S2 and Fig. S3). The number of observations for each of these *t*-tests varied daily based on the number of paired count station observations available on any given day. The number of observations ranged from a minimum of 48 to a maximum of 54. The median number of observations was 52 stations, with a mean of 51.76 ± 1.12 stations. Fig. S2 shows the paired, two tailed t-test results for traffic between 2019 and 2020, classified by vehicle class. The findings suggest that prior to mid-March of 2020, traffic was only nominally different between years, with few instances of significant difference. Since mid-March and corresponding to the Governor's emergency declaration, differences in traffic began to emerge. In general, the impact of the pandemic on traffic varied according to vehicle size. The findings suggest the impact of the pandemic on traffic was less on larger vehicles. Starting as early as March 12th, Class 2 vehicles were significantly lower than prior year's levels. Differences in Class 2 vehicle traffic between years persisted, with few exceptions, until the end of the analysis period on August 31st, 2020. Class 5 vehicles deviated from prior year levels starting from mid-March and continued until the end of May. The months of June and July exhibited some instances where Class 5 vehicles returned to pre-pandemic levels, while August showed minor differences between the years. Significant changes in Class 8 vehicles were not as pronounced until the last week of March and returned to normal conditions much earlier, beginning, to varying degrees, in May and June. By July, Class 8 vehicles had approximately returned to 2019 levels, even exceeding them in some instances. Class 9 vehicles do not appear to have been impacted by the pandemic until April and were restored to pre-pandemic levels by May, with few exceptions.

Each vehicle class plays a unique role in Florida's economy and produces its own signature of pollutant emissions. Class 2 vehicles, passenger vehicles used predominantly by commuters and account for the majority of vehicles on the roadway, decreased during most of the year. On the other hand, heavy vehicles could result in more severe air pollution (Yang et al., 2021) and these increased after May of 2020. With businesses closed and many commuters working from home during the lockdown, many of these drivers remained at home. Larger vehicles, by contrast, are commercially operated. The need for commercial shipping likely increased as the pandemic persisted, as people began to adapt to social distancing and business closures. This is evident in the fact that June, July, and August of 2020 exhibited increases in the volume of Classes 8 and 9 vehicles above their 2019 levels. It is also important to note that while overall traffic significantly decreased during most of the year in 2020, large vehicle classes did not follow this trend.

3.3. Social indicator overview

Fig. 4 illustrates a 7-day moving average number of original Tweets containing the keywords, phrases, or hashtags “asthma”, “air quality”, “air pollution”, and/or “cleanair”. Fig. 4 shows that there is a marked difference between the largely uniform levels of 2019 (represented by the blue line of 7-day moving average and the black line of best fit) and 2020. The 7-day moving average for 2020 departs significantly from the 2019 data with two major departures demonstrating steep immediate increases and slow returns, directly following (1) 3/15/2020 and (2) 6/19/2020 as shown by the green dotted lines on Fig. 4. These two immediate increases correspond to the beginning date of the lockdown in Florida and to Phase 2 of Florida's reopening plan which began on June 5, 2020, respectively. It is to be noted that Florida's Phase 1 re-opening was initiated on May 4, 2020 and subsequently updated on May 15, 2020. This order allowed for the reopening of nearly 80% of the state parks and permitted hospitals to conduct elective surgeries. Retail establishments, bars, and restaurants were also permitted to reopen at 25% capacity (Fla. Exec. Order, 2020a). Phase 2 of Florida's reopening plan began on June 5, 2020 for most of the state and allowed for 50% capacity at bars and restaurants as well as the return to full capacity at gyms, retail establishments and most other industries (Fla. Exec. Order, 2020b). In addition to a purely quantitative rise in the number of Tweets, the ways in which Tweets characterized air quality showed a marked change using qualitative content analysis.

In 2019, the content of the Air Quality Tweets demonstrated some concern over governmental regulation of vehicle emissions. Many of these Tweets, especially political arguments, cited scientific research to justify claims, though several more Tweets described personal somatic experiences of rush hour gridlock as “deadly air pollution.” Politically, the Tweets focused on national and international politics. Tweets explicitly categorized air pollution as a “national security risk.” China and other locations were cited as “culprits” for relaxed vehicle emissions that fail U.S. standards. Solutions-oriented discourse discussed the merits of various incentive policies to move toward better single-user-vehicle standards. These Tweets advocated improving air quality through political stances explicitly tied to socialist environmental justice by strengthening public transportation and reducing pollution from economically advantaged single-user-vehicle owners. Criticisms about air quality and rideshare programs were largely limited to exposure to second-hand and third-hand cigarette smoke from drivers. Multi-user rideshare programs were largely promoted as solutions to traffic congestion and air pollution.

In the months of 2020 before the lockdown, the content of the Air Quality Tweets was largely national and hyper-local in scale focusing on cultural consumption standards and political responsibility. Earlier in the year, local concerns were around urban air pollution during The Miami Grand Prix, pointing the finger at personal vehicle extremes. As COVID-19 pandemic grew into a worldwide problem affecting local Florida communities there was a shift. One concern was the political failure to protect Americans, specifically family members with higher risks (co-morbidities and/or exposure as essential workers), through longer-term accountability for livable air quality and respiratory healthcare. During the lockdown, the content of the Air Quality Tweets contained more references and science claims than those in 2019 and in 2020 before (and later after) the lockdown. Comparative urban air quality analyses were circulated to publicize the lockdown's effect on improved air quality and pollution dissipation. Tweets cited a sense of urban residents' “disbelief” at the visible, auditory, and palpable conditions with fewer air pollution sources. Some Tweets used these as “proof” that high volumes of single-user-vehicles among growing urban populations are “destroying our planet.” Environmental “healing,” with particular reference to fewer cars and better air quality, was cited as a “pro” offsetting the myriad “cons” of the lockdown. Some promoted out-of-the-box solutions for repurposing vehicle lanes into two-way bike lanes in major cities to address COVID-19 risks on public transit and air pollution. People reiterated that re-imagining urban life and infrastructures was a “beneficial side to the virus,” some hoping that the air quality improvements evident during the lockdown would lower perceived dependency on gas cars.

In the months after the lockdown, the content of the Air Quality Tweets was critical of governmental spending on personal vehicle infrastructural improvements and reduplication. This demonstrates a continued valuation for public transportation systems, despite the transportation and public health challenges of the COVID-19 pandemic. Other Tweets focused on adapting single-user-vehicles for a better air quality. There were some arguments for electric personal vehicles that drew on people's visceral, embodied experiences of seeing the sky more clearly, implying this was not a hypothetical future, but an achievable reality after collectively witnessing the palpable changes. Importantly, the health-based arguments to traditional vehicle air pollution were not linked to the COVID-19 pandemic, rather to less politically charged health issues. Other suggested adaptations included that rideshare companies should fund zero-emissions vehicle technologies for drivers, reminding people of their personal experience with better air quality during quarantine. Some Tweets prescribed economic and policy interventions. During Earth Day, the conversation was politicized and used essentialist language at higher rates. In a list of the 6 ways Mother Earth was “healing” during quarantine, traffic-related aspects made up over half of the list (such as air pollution slowed, roads emptier, emissions decreased, and city soundscapes changed).

As people shared their first-hand experiences with the COVID-19 stay-at-home orders, Floridians in metropolitan areas demonstrated quantitative changes in their Tweets about air quality and asthma. Each shift, both into and out of the lockdown, was preceded by a spike in discourse not comparable

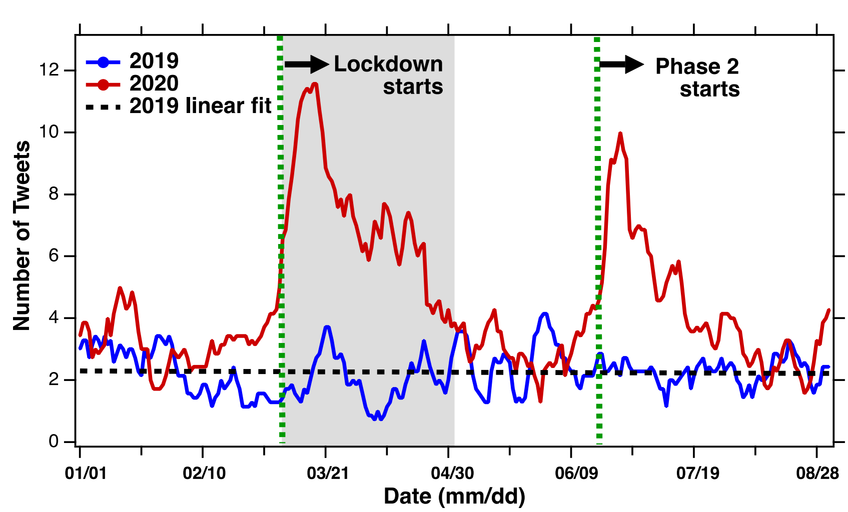

Fig. 4. A time series of the 7-day moving average for the number of keyword Tweets comparing 2019 and 2020. The beginning and end of the complete lockdown period are followed by steep increases in Tweets related to air quality, shown in green dotted lines. Note the spike begins during the emergency declaration. Gray shaded area represents the period of complete lockdown (15th March–30th April).

with historic discourse records. But beyond simply quantitatively increasing the number of mentions on social media, it is important to note that the qualitative record showed that people were talking about air quality, vehicles, and traffic in different ways. Personal accounts sought to provide somatic evidence (sensory data on smell, sight) to reflect the global mainstream media stories about environmental "healing" as fewer cars were on the road. The broader shifts in reduced personal vehicle traffic were described in Tweets as the reasons for this, but none explicitly analyzed the changing patterns of large vehicle mobility patterns.

3.4. Air quality indicators correlation analysis

In this section, we test the correlation between the three air quality indicators, atmospheric pollutant concentrations, traffic count including vehicle classifications, and air quality tweets to identify inter-relationships between the indicators. The correlation was tested using Pearson's correlation coefficient (r) between parameters during three distinct periods, namely (1) Pre-lockdown: January 1st - March 14th, (2) Lockdown: March 15th - April 30th, and (3) Post-lockdown: May 1st - August 30th. Fig. 5 shows a detailed correlation matrix for these indicators during the three periods. For comparison purposes, a weak correlation was defined as this corresponding to an r of less than ± 0.3 and shown in Fig. 5 in blue color. A moderate correlation was defined as $\pm 0.3 < r < \pm 0.6$ and shown in Fig. 5 in red color. As for a strong correlation, this was defined as one with a value of $r > \pm 0.6$ and depicted in Fig. 5 in green color. Details of monthly correlations for NO_2, $PM_{2.5}$, O_3, and CO concentrations and monthly vehicle count associated with each vehicle class are presented in Tables S3 through S6, respectively. Correlations between monthly concentrations of atmospheric pollutants and air quality tweets are reported in Table S7.

It could be deduced from Fig. 5a that before the lockdown, there was no distinct correlation between air quality, traffic, and tweets except for moderate to strong correlations between O_3 and both traffic and tweets. However, this behavior has changed during the lockdown (Fig. 5b), where moderate to strong correlations were manifested between all three indicators. For example, O_3 - traffic correlations diminished during the lockdown and instead NO_2 - traffic correlations were emphasized. This is especially true for correlations between NO_2 levels and heavy vehicles (Yang et al., 2021). The positive correlations between NO_2 and traffic is expected in the U.S. because vehicles emit NO directly into the atmosphere which is oxidized in the atmosphere to form NO_2. As for $PM_{2.5}$ concentrations, these exhibited moderate negative correlations with all vehicle classes ($r > \pm 0.3$). This might indicate that the primary particle pollution was related to traffic from all classes, especially for Class 2 vehicles. It might also infer that secondary processes were responsible for the formation of $PM_{2.5}$ during this period. The same trend was observed for AQI and traffic correlations in accord with previous observations (Chen et al., 2021). The negative relationship between the general air quality indicator (i.e., AQI), particle pollution (i.e., $PM_{2.5}$ concentrations), and tweets might suggest one of two hypotheses, either that people are no longer communicating about air quality as it deteriorates or that people are not aware of the difference between a good versus a bad air quality day. However, more rigorous sentiment analyses are needed to test these hypotheses. Collectively, the positive correlations between traffic and tweets and the subsequent relation between NO_2 and tweets might infer that people were relating the number of vehicles to air quality during the lockdown. Although correlations displayed a decrease after the lockdown, they were still stronger compared to the period before the lockdown (Fig. 5c). Traffic was positively correlated with CO rather than NO_2 and negatively correlated with O_3 in this period. Tweets were positively correlated with both AQI and $PM_{2.5}$ levels. During the post-lockdown, the decreases in traffic-tweet correlations might indicate that people no longer perceived air quality depending on the number of vehicles on the road.

Overall, during and after the lockdown, as vehicle class use fluctuated, so did atmospheric pollutants related to traffic, providing a range of pollutant intensities and varieties detectable by sampling instruments. Although the pollutant signatures of each vehicle class were detectable to air quality sensors, they were not demonstrated as observable to people. Instead, Tweets about air quality and asthma–which quantitatively were comparatively stable in 2019–did not spike as air quality monitors registered major disruptions expected from vehicle emissions. Rather, Tweets spiked as passenger vehicle traffic dropped. This demonstrates several critical points. First, this shows that some pollutants are directly observable by people (e.g., $PM_{2.5}$) and some are not (e.g., NO_2). Some pollutants are linked to the number and type of vehicles on the roadway, which varies by time of day, day of week, and season. On the other hand, other pollutants are not associated with vehicular emissions but rather emitted from other sources. It also indicates that Tweets about air quality and asthma symptoms may be a reaction to the number of passenger cars observed on the road, and not a reliable indicator about air quality as a somatic or embodied reaction to exposure to pollutants. This is corroborated by integrating the qualitative content analysis of the Tweets from different emissions contexts, which shows changing philosophies of air pollution causes and rationales for their mitigation.

4. Conclusions

Air quality is a complicated process that involves several pollutants, complex chemistry, and meteorological influences which significantly affects community health and living standards. This novel research brings

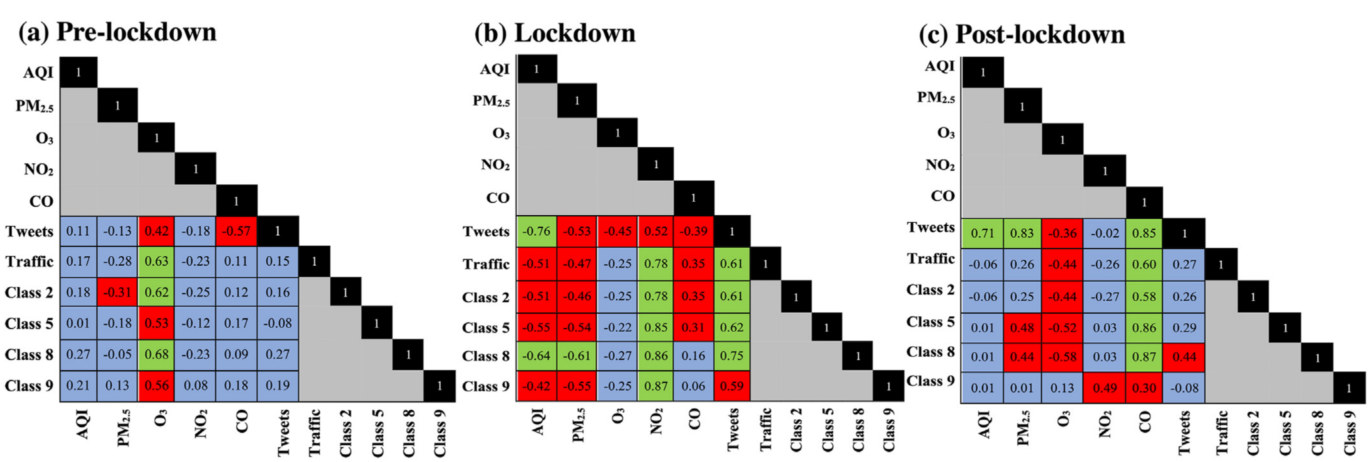

Fig. 5. Correlation matrix of atmospheric pollutant measurements, traffic, and air tweets as air quality indicators during the (a) pre-lockdown, (b) lockdown, and (c) post-lockdown periods. Light blue color refers to a weak correlation corresponding to a Pearson's correlation coefficient (r) less than ± 0.3, red color refers to a moderate correlation ($\pm 0.3 < r < \pm 0.6$), and green color refers to a strong correlation ($r > \pm 0.6$).

together interdisciplinary air quality, traffic, and social media data during a time of monumental change to measure the relationship between pollution emissions, concentrations, and their impact on the perceived quality of the air within Florida's cities. Not only do the results herein yield interesting findings and useful implications to each specific indicator, but more interestingly provide promising results in integrating these indicators as part of a holistic system. These results do not prove any causal relationships, though the strong correlations point to the promise of integrating indicators. While people's perception might have been correlated with specific atmospheric pollutants, especially those from vehicular exhaust, people fail to correlate with a more general indicator (i.e., AQI) and with many other criteria pollutants due to the convoluted processes in the atmosphere. Our results show that the correlation between traffic, pollutant concentration, and air quality-related tweets became significantly stronger after the start of the lockdown period and continued after the end of the lockdown in Florida. As traffic decreased during the lockdowns, improvements in specific pollutants (i.e., NO_2 and CO) were observed as well as an uptick in tweets related to air quality and breathing. This suggests a residual increase in public awareness persisting beyond the initial onset of the pandemic and may serve as a building block for engaging the public on matters related to air quality and emission standards. In terms of public discourse, the strong correlation between air quality tweets and reductions in traffic suggest Floridians were likely associating lower traffic volumes with better air quality, regardless of actual pollutant concentrations. Overall, it could be deduced from this study that while social media discourse did not prove to be a predictor of actual air quality, it did show promise as an indicator for volume of personal vehicle traffic, particularly in areas without adequate surface monitoring stations. Further, this work demonstrated an increase in positive environmental sentiment during changes to stay-at-home orders. While people's perceptions would likely improve with fewer vehicles, it ought not be used as a reliable indicator for human health-related studies. In conclusion, a significant find of this research is demonstrating the disparity between air quality metrics and discourse about human wellbeing and the need for raising awareness to combat the detrimental impacts of atmospheric pollution and climate change.

Declaration of competing interest

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CRediT authorship contribution statement

Heather O'Leary: Conceptualization; Social Media data curation; Codebook construction; Formal content analysis; (N)etnography Methodology; Social Media data Validation; Visualization; Writing - original draft, **Scott Parr:** Conceptualization; Traffic data curation; Formal analysis; Resources; Validation; Visualization; Writing - original draft, and **Marwa M. H. El-Sayed:** Conceptualization; Air Quality data curation; Formal analysis; Methodology; Resources; Software; Validation; Visualization; Writing - original draft; Writing - review & editing.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.scitotenv.2022.154209.

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