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Statewide assessment of air quality changes in Florida during the COVID-19 pandemic

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ABSTRACT

The COVID-19 pandemic has forced many countries from all over the world to adopt extreme measures to suppress the spread of the pandemic. These measures have triggered changes in air quality. Many studies showed an overall short-term improvement in air quality. This study investigates the long and short-term impacts of COVID-19 pandemic on air quality in the State of Florida. Three air quality indicators (AQI) from 69 stations located in 30 counties in the State of Florida were analyzed for 2015–2021. These pollutants are Fine Particulate Matters ($PM_{2.5}$), Nitrogen Dioxide (NO_2), and Sulfur Dioxide (SO_2). The long-term changes in pollutant levels were assessed via Time-Lag linear regression analysis (TLR). The results show that $PM_{2.5}$ levels dropped from 8.88 to 8.24 μg/m^3 between 2015 and 2021. However, the ANCOVA test shows that the TLR's slope for $PM_{2.5}$ is insignificant, with a p-value of 0.859. Thus, there was no statistical evidence that the changes in 2020 and 2021 differ from previous years. NO_2 levels fluctuated over the study period between 13.0 and 16.0 ppm with no identified trend. Nonetheless, the regression slope was also insignificant, with a significance of 0.401. The average SO_2 concentrations steadily dropped from 4.3 ppb in 2015 to 2.0 ppb in 2020 and 2.62 ppb in 2021, with a regression slope significance of 0.001. It is concluded that pollutants' levels behave differently during the lockdown and release periods, indicating that the lockdown contribution to reduce industrial activities is reflected on air quality rather than mobile source emissions.

1. Introduction

The end of 2019 will be remembered in history as the time when a new global pandemic broke out. This new pandemic is commonly known as COVID-19 pandemic, which is a global spread of a virus that attacks the respiratory system of humans, causing severe health issues. The first case of COVID-19 viral pandemic was officially diagnosed in China in December 2019 [1,2]. The pandemic spread rapidly and globally soon afterwards, reaching most of the countries. Hundreds of millions of humans were infected with this virus. Millions of lives were lost, and most of the infected humans suffered from severe respiratory malfunctioning symptoms [1–4].

As a result of the wide pandemic spread, authorities from all over the world have imposed certain measures and lockdowns, directly affecting the daily activities [3–7]. Remote work environment was widely promoted, and education sectors adopted online education schemes. Land transport, logistics, and air travels were either restricted or fully suspended [3,4]. As a result of the changes in daily activities, it is expected to have an indirect influence on the quality of air due to the significant reduction of socioeconomic activities (such as motorized mobility, constructions, and industrial activities) that would normally contribute to air pollutants [8–10].

The State of Florida is the third largest state in the United States in terms of population, one of the 10th highest states in terms of population density. Furthermore, the State of Florida is ranked second in population and density of senior citizens (aged 65 years or more), which is the age group that are severely affected by COVID-19 virus infection and associated symptoms, health issues that are related to the quality of air [11–13]. Thus, the research question being formulated in this study is to assess the changes in pollutants' levels during the pandemic, and to

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identify if those changes are associated with the pandemic, or a result of long-term trend of reducing these pollutants. This study aims to evaluate the short-term and long-term changes in air quality during the COVID-19 pandemic lockdown and release periods in the State of Florida.

The United States confirmed the first positive case on January 20, 2020 from a sample that was taken two days before [14], and the first positive case in the State of Florida was confirmed on March 1, 2020 [15]. However, the impacts of COVID-19 pandemic and the corresponding preventive measures varied widely across the different states the USA, where each state adopted different response measures with different restriction levels [16].

2. Literature review

Many studies have examined the impact of COVID-19 pandemic and lockdown on air quality all over the world. Although a reduction in pollutants' levels was globally noticed, the levels of Fine Particulate Matters ($PM_{2.5}$) and Nitrogen Dioxide (NO_2) were substantially reduced [17–19]. A global comparison of Carbon Dioxide (CO_2) levels showed significant short-term reduction [9]. While some studies have reported a global air quality improvement, most of the studies have evaluated air quality before and after the pandemic in specific region or country, such as the studies from North and South America, Europe, Africa, East and South Asia, and the Middle East.

In the United States, the comparison of states with and without stay-at-home orders showed that the states with longer period of restrictive measures showed higher improvement in air quality levels [20]. A significant overall air quality improvement in the State of California was reported [21]. As for the State of Florida, one study has reported significant reduction in different pollutants (namely, $PM_{2.5}$, NO_2, Sulfur Dioxide (SO_2), Ground Ozone (O_3), and Carbon Monoxide (CO)) across six major Florida cities [22]. In the City of New York, a study found no significant changes in long-term $PM_{2.5}$ and NO_2 levels during the first five months of 2020 compared to the same months between 2015 and 2019 [23]. Although the levels of these two pollutants in the City of New York were reduced, there was a general trend of declining $PM_{2.5}$ and NO_2 levels since 2015. In Canada, a comparison between the year of 2020 and two previous years showed strong relationship of Air Quality Health Index (AQHI), NO_2 and CO levels with the COVID-19, however no significant changes in SO_2 levels were found [24].

In Italy, pollutants' levels showed an overall air quality improvement during the lockdown in 2020 when compared to the same period between 2017 and 2019 [25]. A comparison of NO_2 levels in 2020 and 2015–2019 showed significant improvement around schools in UK [26]. In Spain, higher reduction in NO_2 levels was observed compared to Particulate Matter (PM_{10}) levels reduction [27]. Moreover, changes in Ozone levels were not uniform across different cities in Spain [27]. In Portugal, the NO_2 levels followed a similar trend to the one observed in Spain, where the reduction in NO_2 levels was higher than the reduction of PM_{10} levels [27].

A study from Brazil found that the variations in pollutant's levels are related to the dynamics of atmosphere at various time scales in the State of Sao Paulo [28]. This study also assessed the factors driving the reduction in pollutant levels. Another study in Rio de Janeiro found that CO and NO_2 levels have declined during the lockdown period when compared to the same period from previous years due to reduction of vehicular usage [29]. However, $PM_{2.5}$ reduction was only observed during the first week of lockdown.

A comparison of pollutants' levels between the year of 2020 and 2019 showed that air pollution levels in China were reduced drastically for all pollutants ($PM_{2.5}$, PM_{10}, NO_2, SO_2 and CO) except ozone [30]. However, this reduction is characterized as a short-term reduction. A similar trend was also observed in Korea, with the only exception of SO_2 [31]. A reduction of pollutants levels ($PM_{2.5}$, PM_{10}, NO_2 and O_3) was observed in Thailand during the first three weeks of the lockdown in 2020 [32]. Bhatti et al. (2023) investigated the effects of socioeconomic factors on air pollution in China [33]. The study suggests that socioeconomic factors need to be considered when developing policies to reduce air pollution in China. Bhatti et al. (2022) studied the change in air quality patterns in Anhui Province, China, during the COVID-19 pandemic [34]. They found that air pollution levels decreased significantly during the pandemic, mainly due to the reduction in human activities. Aamir et al. (2021) conducted a similar study in Hubei Province, China, and found similar results [35].

One study from Africa reported that the seasonal changes in meteorological conditions were the main dominant contributors in improving air quality in Nigeria [36]. A study from the Middle East found that the small cities have experienced greater reduction in NO_2, SO_2, and CO levels than the mega cities [37]. In Jordan, $PM_{2.5}$ and NO_2 levels during the first quarter of 2020 were reduced by 29 % and 79 %, respectively compared to the levels of the corresponding quarter in 2019 [38].

Comparison of air pollutants' levels between the year of 2020 and the previous years in Indian cities have shown gradual reduction in $PM_{2.5}$ levels due to lockdown [39]. The study also found that the aerosol optical depth (AOD) changes were not spatially uniform. Another study reported that the lockdown has triggered a sudden reduction of air pollutants in Dhaka, Bangladesh [40]. The NO_2 levels in New Zealand were significantly reduced by 48–54 % during the most restrictive alert level [41].

Galvan et al. (2022) examined the relationship between CO_2 emission, economic growth, and trade openness in middle-income trap countries [42]. They found that CO_2 emission is positively correlated with economic growth and negatively correlated with trade openness.

Nawaz et al. (2021) proposed a hybrid approach to forecast the COVID-19 epidemic trend [43]. The study suggests that the hybrid approach can be used to inform public health policy and decision-making.

In conclusion, most of these studies focused on comparing air quality and pollutants' levels during the lockdown in 2020 against the corresponding levels from previous years (mostly the years of 2015 and 2019). Moreover, the considered air quality indicators varied widely, however, assessing $PM_{2.5}$, NO_2 and SO_2 levels were common in most of the studies. In general, most of the studies have reported an overall air quality improvement during the lockdown period. However, these improvements remain within the context of short-term assessment, and they do not consider the long-term timeline of air quality improvement. On the other hand, some studies found that the changes in pollutants' levels are insignificant compared to the previous years, especially when the long-term changes of these levels are considered. Fig. 1 illustrates a

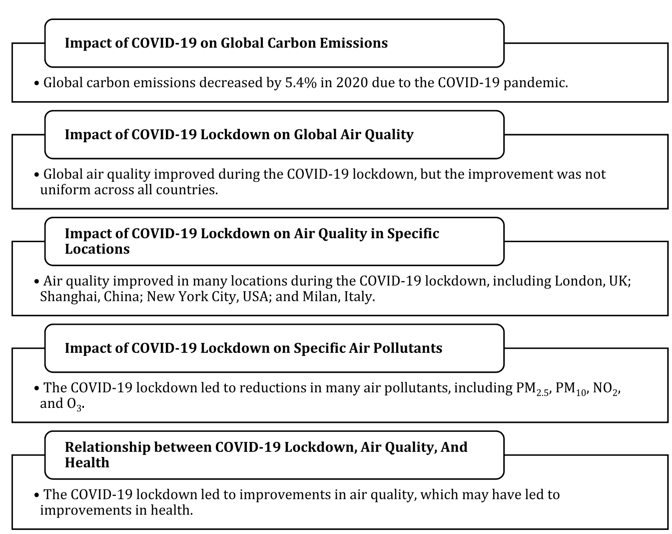

Fig. 1. Literature review graphical summary.

brief summary of the conducted literature review.

3. Study objectives

This study aims to assess if there are any significant changes in air quality during the COVID-19 pandemic in the State of Florida. Three main air quality indicators for the years 2015–2021 are investigated in this assessment. The assessment will verify if there are any changes in air quality over the study period, and if the COVID-19 pandemic has attributed to the changes in air quality, if any. The assessment considers different geographical locations within the State of Florida.

The COVID-19 lockdown is expected to influence certain activities (such as power consumption, motorized mobility, and industrial activities) that are associated with pollutants and air quality. Therefore, this study is targeting the pollutants that are mostly associated with these types of activities. The selected pollutants are Fine Particulate Matters with diameters less than 2.5 μm ($PM_{2.5}$), Nitrogen Dioxide (NO_2), and Sulfur Dioxide (SO_2) as air quality parameters that might be affected by varying socioeconomic activities during COVID-19 [44,45].

Fine particulate matter of 2.5 μm or less in diameter ($PM_{2.5}$) is a dangerous pollutant because it can penetrate the lung barrier and enter the blood system, causing cardiovascular and respiratory disease and cancers [46,47]. It affects more people than other pollutants and has health impacts even at extremely low concentrations [46].

NO_2 is a gas that is mainly emitted from combustion processes such as traffic, power generation and industrial activities [48]. It can cause inflammation of the airways, reduce lung function, and increase the risk of respiratory infections [47]. It can also contribute to the formation of other pollutants such as Ozone and $PM_{2.5}$ [47].

SO_2 is a gas that is mainly emitted from burning fossil fuels that contain sulfur, such as coal and oil. It can cause irritation of the eyes, nose, and throat, bronchoconstriction, and asthma exacerbation. It can also react with other substances in the air to form sulfate aerosols, which are a component of $PM_{2.5}$. Although it would be expected to observe reduction in air pollutants levels during the COVID-19 lockdown, it is particularly important to verify if those reductions are attributed to other factors, such as seasonality, climate changes, short-term changes in socioeconomic activities, and the implemented environmental policies and regulations rather than the lockdown itself. This objective can be met by comparing these concentrations with previously observed trends and assessing the statistical significance of the changes over time.

4. Materials and methods

4.1. Study approach

This study investigates the levels of three pollutants that are highly attributed to the restricted socioeconomic activities (i.e., $PM_{2.5}$, NO_2, and SO_2). Daily measurements for the years of 2015–2021 were collected from different monitoring stations that are distributed across the State of Florida. To account for both short-term and long-term changes, the study period covers five previous years before the start of the pandemic, and two years after the pandemic, which includes the lockdown period in 2020 and the release measures period in 2021.

As the main objectives of this study are identified, the following approach is used in this study. Air monitoring sites in Florida have been identified. The data available from these sites were reviewed and filtered to assure that sufficient data are available to cover the daily levels of pollutants between 2015 and 2021. Fig. 2 Summarizes the approach used in this study.

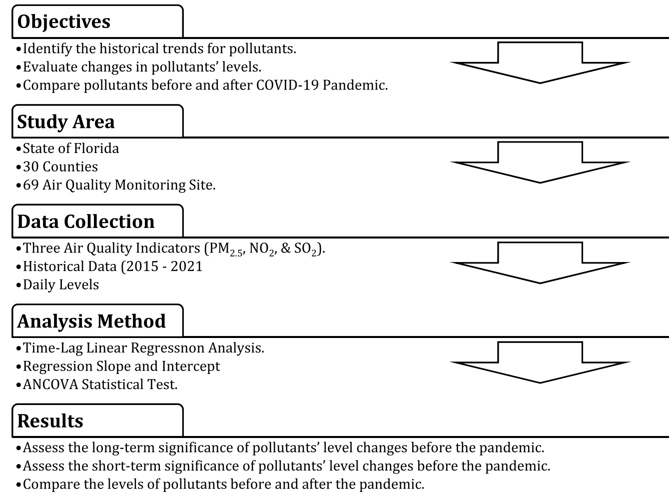

Fig. 2. Study approach graphical summary.

4.2. Selected air pollution parameters

The Air Quality Index (AQI) is one of the most popular air quality indicators identified based on particulate matter ($PM_{10} and PM_{2.5}$) and the concentration of some chemicals including Sulfur Dioxide (SO_2), Nitrogen Dioxide (NO_2), Ground Ozone (O_3), and Carbon Monoxide (CO). AQI values start from 0 for ideal air quality up to 500 when air pollution can cause an instant danger to the public. As reported by American Lung Association, AQI and its contributing pollutants concentrations are monitored and reported daily in more than 800 counties (out of 3143 counties in the United States [49]) [13]. The AQI categorizes air pollution levels into Good, Moderate, Unhealthy for Sensitive Groups, Unhealthy and Very Unhealthy [13]. The importance of this indicator justifies the necessity of recording $PM_{2.5}$, NO_2, and SO_2 levels.

United States Clean Air Act (CAA) and Environmental Protection Agency (EPA) have set National Ambient Air Quality Standards (NAAQS) for Primary and Secondary standards. Enforceable Primary Standard addresses public health protection associated with air quality including the health of sensitive population such as elderly, children, and asthmatics. However, unenforceable Secondary Standard attempts to address public welfare protection against damage to properties, farms, and animals as well as declined visibility, known as essential parameter in transportation safety. Table 1 shows NAAQS Standard for major pollutants of concern in ambient air [50]. Table 1 also reports NAAQS's Primary and Secondary standard for major pollutants in ambient air. The maximum allowable concentration of $PM_{2.5}$ and PM_{10} are 12.0 μg/m^3 and 150 μg/m^3, respectively are also reported. It is worth mentioning that the levels of $PM_{2.5}$ are declining, and its average has been below the national standards since 2006, with a 37 % national decrease between 2000 and 2021, and 45 % decrease in Southeast regional average [51].

The concentrations of particulate matter with sizes smaller or equal 10 μm and 2.5 μm are called PM_{10} and $PM_{2.5}$, respectively [52]. Such inhalable particles are made of a variety of different chemicals and may appear in distinct sizes and shapes. PM_{10} is a great indicator of the presence of dust, pollen, and mold in ambient air, known as an indicator for natural sources of pollutants, whereas $PM_{2.5}$ indicates the abundance of smaller particles such as combustion particles, organic compounds, and metals. $PM_{2.5}$ is an indicator that is more relevant to human-induced pollution than PM_{10}. Unpaved roads, earth works and construction sites, fire, industrial smokestacks are identified as the main sources of direct emission of particulate matter called primary pollutants. However, a variety of particles are generated in the atmosphere due to the occurrence of complex reactions of chemicals such as nitrogen oxides and sulfur dioxide that were already emitted to the air from automobiles, industries, and power plants. These pollutants are called secondary particulate pollutants and tracking the contribution of secondary pollution sources is neither direct nor straightforward [52].

$PM_{2.5}$ and PM_{10} are functions of both natural characteristics of the region, such as the lands' soil properties, wind intensity and direction,

Table 1
Summary of maximum allowable pollutants' levels [50].

Pollutant	Primary/ Secondary	Averaging Time	Level	Form
Carbon Monoxide (CO)	Primary	8 h	9 ppm[a]	- Not to be exceeded more than once per year.
		1 h	35 ppm-	
Nitrogen Dioxide (NO_2)	Primary	1 h	100 ppb [b]	– 98th percentile of 1-h daily maximum concentrations, averaged over 3 years.
	Primary Secondary	1 year	53 ppb	- Annual Mean.
Ozone (O_3)	Primary Secondary	8 h	0.070 ppm	- Annual fourth-highest daily maximum 8-h concentration, averaged over 3 years.
Particulate Matter ($PM_{2.5}$)	Primary	1 year	12.0 μg/m^3	- annual mean, averaged over 3 years.
	Secondary	1 year	15.0 μg/m^3	- annual mean, averaged over 3 years.
	Primary Secondary	24 h	35 μg/m^3	– 98th percentile, averaged over 3 years.
Particulate Matter (PM_{10})	Primary Secondary	24 h	150 μg/m^3	- Not to be exceeded more than once per year on average over 3 years.
Sulfur Dioxide (SO_2)	Primary	1 h	75 ppb	– 99th percentile of 1-h daily maximum concentrations, averaged over 3 years.
	Secondary	3 h	0.5 ppm	- Not to be exceeded more than once per year.

[a] ppm: Parts per Million.
[b] ppb: Parts per Billion.

and socioeconomic activities such as industrial emission, construction earth works and traffic flow in unpaved roads. The long-term assessment of air pollutant's level in many locations revealed significant seasonal variations, suggesting considerable impact of natural parameters such as humidity, precipitation, and soil moisture content, especially on PM_{10} levels. Zhan et al. reported that natural factors play a greater role on air pollution including particulate matters as compared to socioeconomic factors [53]. According to above-mentioned information, $PM_{2.5}$ deemed to be a better indicator of human-induced air pollutants to be studied in this research.

Nitrogen Oxides (commonly shown as NO_x) are known as toxic and very reactive gases generated when fuel is burned at high temperatures in combustion systems such as automobiles, trucks, power plants, industrial boilers, cement kilns, and turbines. As presented in Table 1, NO_x concentrations in atmosphere are regulated by NAAQS standards. It is a strong oxidizing agent and plays a key role in the generation of ozone (smog) on hot summer days. NO_x concentration is a great indicator of human-induced air pollutants. As reported by EPA, the regional average concentration of NO_2 decreased as much as 64 % from 2000 to 2020 due to attention to the implementation relevant air quality regulation [54]. The annual 99th percentile of daily maximum 1-h average concentration of NO_2 is mostly below 50 ppb, which is below maximum allowable concentration of 53 ppb set by EPA [54].

NAAQS standards for SO_2 are set to protect against exposure to all gaseous sulfur oxides including SO_2, known as the component of greatest concern. As reported by EPA, the regional average concentration of SO_2 decreased as much as 86 % from 2000 to 2020 due to attention to the implementation relevant air quality regulation [55]. The annual 99th percentile of daily maximum 1-h average concentration of SO_2 is below 25 ppb, which is below maximum allowable concentration 75 ppb set by EPA [50]. The major sources of SO_2 pollution are from coal, oil and diesel combustion at power plants and other industrial facilities [56]. Rare natural sulfur dioxide emission can only occur due to volcanic activity; hence natural emission of SO_2 is highly unlikely in most of counties and SO_2 pollution is known as human-induced pollution [55]. Once emitted into the air, sulfur dioxide also contributes to secondary pollutants including sulfate aerosols, particulate matter, and acid rain. Sulfur dioxide concentration in downwind ground-level has direct correlation with socioeconomic factors including industrial facilities in that vicinity [8]. Combustion of diesel equipment and vehicles were one of the main sources of sulfur dioxides in the United States till nationwide regulation for reducing sulfur content of diesel fuels was enacted. Consequently, annual sulfur dioxide (SO_2) emissions from road vehicles in the United States decreased from 503 to 15 thousand tons from 1990 to 2021 [57].

4.3. Study area characteristics

The State of Florida, located in the south-eastern part of the United States of America, has most of its land as a peninsula between the Atlantic Ocean and the Gulf of Mexico. The state consists of 67 counties, representing different metropolitan configurations.

The US state of Florida with average size of 170,312 km^2 area is known as the third populated state with a population of 21.22 million. The southern part of the state has a tropical climate, while the rest of the state has a humid tropical climate. The rainy season starts in May and continues till October. During July, dust from African Sahara moves to the state, suppresses rainfall, and negatively impacts on Florida's air quality, which is known as one of the cleanest in the country. According to World Resource institute, the State of Florida is among top ten Greenhouse gas (GHG) emitting states with quantity of 267.24 million ton of GHG where 41.7 % of GHG are emitted by transportation sectors and 37.4 % are emitted by power and heat generators [58]. The share of these sectors indicates that any noticeable variation in their performance might affect the air quality of surrounding environment.

The average GHG emission of the State of Florida in 2019 is 11.01 metric tons of CO_2 per capita, which is lower than the country's average emission of 15.30 metric tons of CO_2 per capita [59,60]. This implies that average emission of SO_2 and NO_x by individuals in different sectors such transportation and electricity generating sectors might be also milder compared with many other states in the country.

4.4. Analysis approach

The study period consists of seven consecutive years (from 2015 to 2021), to represent five years before the spread of COVID-19 pandemic, and two years after the spread of COVID-19. Historically, there were 104 ambient air monitoring sites, were some of the sites are no longer operating [61]. These sites were reviewed and filtered to assess the availability of data during the study period. Air quality indicator data were collected from 69 air quality monitoring stations. These stations are distributed at various locations with the State of Florida, covering a wide range of metropolitan areas, land uses, and population densities [61–63]. However, these stations were neither fully active nor measuring the same type of pollutants during the study period. Since not all monitoring stations measured all the targeted pollutants' levels, the number of monitoring stations and the included counties varied across the three different pollutants. $PM_{2.5}$ levels were measured in 51 stations (28 counties), NO_2 levels were measured in 15 stations (7 counties), and SO_2 levels were measured in 22 stations (14 counties). The monitoring stations are tracking levels of different pollutants, such as $PM_{2.5}$, SO_2, NO_2, CO, *Ground Ozone*, and PM_{10} at an hourly basis. Most stations are tracking $PM_{2.5}$ levels. However, fewer stations are tracking NO_2, and SO_2, since some of the stations are limited to monitor only one or two types of pollutants. Therefore, this study is limited to these three types of pollutants, which are known to be air quality indicators that are sensitive to changes in socioeconomic activities [44,64].

4.5. Historical trends of the main air quality indicators

Fig. 3 (a) shows the monthly changes in $PM_{2.5}$ between 2015 and 2021. For instance, $PM_{2.5}$ concentrations tend to be at the lower side during the winter, and then as the temperature increases during the summer, its concentrations tend to increase slightly. However, $PM_{2.5}$ monthly average did not exceed maximum allowable concentration of 12 μg/m^3 during the study period. Without exception, $PM_{2.5}$ increased around the month of June, which might be due to expected annual African Sahara dust breakout at this time of the summer. Although such dust breakout is better monitored by PM_{10}, $PM_{2.5}$ records can also detect such natural and rather recurring air quality deterioration. As discussed earlier, $PM_{2.5}$ is not a perfect indicator of socioeconomic activities (such as motorized mobility), since it is frequently interrupted by natural dust generated locally or regionally. Despite the seasonality trend within each of the assessed years, the $PM_{2.5}$ levels tend to be reduced over time.

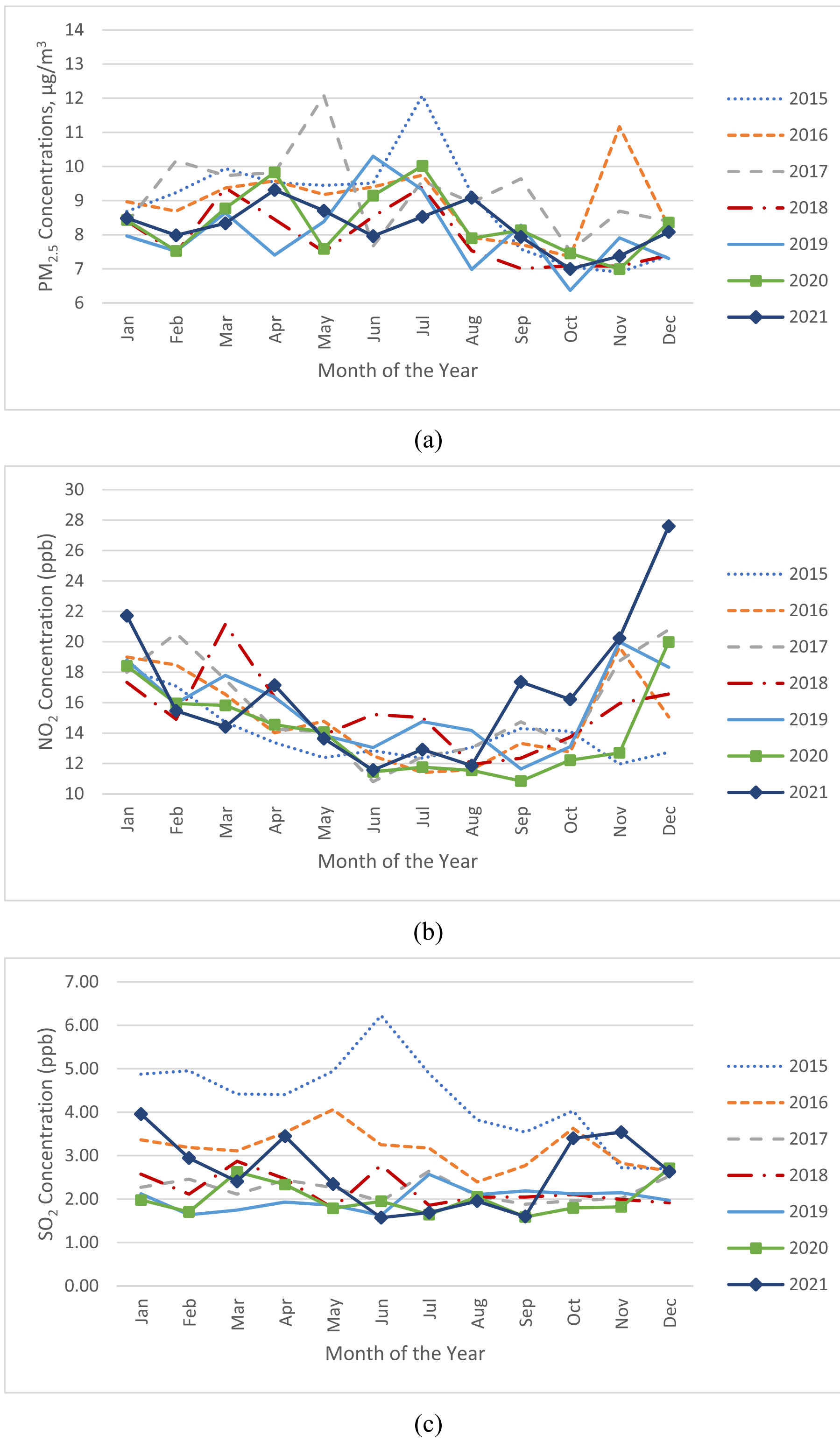

Fig. 3. Monthly Variation of (a) $PM_{2.5}$, (b) NO_2 , and (c) SO_2 levels for each year (2015–2021).

This trend is consistent with the EPA documentations, which indicates that the annual fine particle concentrations across the United States have been declining [51].

Fig. 3 (b) shows the concentrations of NO_2 from 2015 to 2021. The results reveal that the monthly average concentrations of this pollutant did not reach maximum allowable concentration of 53 ppm. As for NO_2 concentrations, there is a clear trend of having low concentrations during the summer months. Some studies reported higher concentrations of NO_2 during fall and winter in the United States and other places [23]. The lower concentration of NO_2 can be associated with its conversion to secondary pollutants such as ground-level ozone during hot season [65].

Fig. 3 (c) shows concentrations of SO_2 from 2015 to 2021. The results reveal that the monthly average concentrations did not reach the maximum allowable concentration of 75 ppb. As for the SO_2 concentrations, the variation within the year is less than the observed trend for the other pollutants. However, the SO_2 concentrations during the winter month of 2021 have experienced higher values than the other months. Moreover, the SO_2 concentrations seem to have more reduction over the years than the other two pollutants. Similar annual reduction of SO_2 is reported as a result of implementing nationwide regulation for reducing sulfur content of diesel fuels since 2000. Enacting the regulation resulted in reduction of SO_2 annual emissions from road vehicles from 503 thousand tons in 1990 to 15 thousands in 2021 [58]. Although the emission of SO_2 depends on the rate of fossil fuels combustion, its concentration in ambient air is also affected by seasonal variation and meteorological factors such as wind speed, precipitation, and rate of its conversion to secondary air pollutants in hot seasons [66].

In general, there is a descending trend of pollutants' levels over the years. Therefore, a statistical comparison between concentrations before and during the COVID-19 lockdown and measures can only reveal the significance of short-term impact, where any potential reduction in those levels in 2020 and 2021 as a result of other environmental regulations cannot be verified.

4.6. Time-lag linear regression analysis model

To verify the long-term changes in $PM_{2.5}$, NO_2, and SO_2 levels, time-lag linear regression analysis (TLR) approach is used. First, the daily averages of statewide pollutants' concentrations across the data collected from all available stations for the years of 2015–2021 are estimated. Then, a separate TLR model is developed for each type of the pollutants assessed in this study. The y-intercept and the slope for the TLR models and their confidence intervals are reported. For a given pollutant, the regression slopes for 2020 and 2021 TLR models are compared against the previous trends, to assess if significant differences are presented or not. The Type III ANCOVA statistical test is performed to test homogeneity changes in y-intercept values and slopes over the years, by examining the interaction between the year and day covariates.

This methodology is used to verify if the changes in a given pollutant's levels are associated with the overall improvement of air quality or short-term changes as a result of COVID-19 pandemic lockdown [51,54,55]. The constants and the slopes for the years of 2015 and 2021 are then compared to draw the conclusion. The TLR general model for the year 2020 can be mathematically expressed in Equation (1). A similar formula is used for the year 2021, where the only difference is the use of one additional previous year (i.e., the year of 2020).

$$P_y = \beta_0 + \beta_X X + \beta_T T_X + \sum_{i=2015}^{y-1} (\beta_{Zi} Z_i + \beta_{XZi} X Z_i) + \varepsilon_y \tag{1}$$

where:

P_y:Concentration of pollutant P in day X for the given year y (years of 2020, 2021).

X:The covariate representing the day of a given year y.

T_X:The time-lag variable value for day X in year y.

Z_i:The dummy variable representing the previous year (i.e., year i).

β_0:The regression model constant.

β_X:The day of year covariate coefficient.

β_T:The time-lag variable coefficient.

β_{Zi}:The year dummy variable coefficient for year i (years 2015–2019).

β_{XZj}:The day-year interaction coefficient for day X and year i (years 2015–2019).

ε_y:Regression analysis error term for year y regression model.

This approach has the advantage of assessing the long-term historical trends of pollutants levels rather than the absolute changes in pollutants levels, or what is called the short-term changes. For example, a pollutant level that has been decreasing steadily over the past decade would be expected to show a further reduction in 2020 due to the COVID-19 pandemic. However, if the analysis only focused on the pollutant level, which reflects the short-term reduction, it would lead to a confounded conclusion that the reduction in this pollutant level is solely attributable to the COVID-19 pandemic, without accounting for the long-term trend of reduction rate. To avoid this bias, this approach evaluates the rates of change of pollutants levels over time and compares them with the expected rates based on the historical data. This way, it can identify any significant deviations from the normal trends that could be linked to the COVID-19 pandemic or other factors. This approach also allows for a more comprehensive and nuanced understanding of the impacts of the COVID-19 pandemic on air quality across different regions and periods.

However, this approach is considering statewide data, which may not account for the spatial heterogeneity of air pollution, which could vary depending on the location, land use, dominating activities, pollutants' source, and meteorology of the pollutants.

4.7. Benefits to society

The benefits of this research for society at large are twofold. First, it provides valuable insights into the long-term changes in pollutants' levels. Moreover, it would also help in identifying the contribution of the lockdown period during the COVID-19 pandemic on those pollutants. As many behavioral, social or industrial activities were significantly impacted at societal level, this research investigates a unique opportunity in providing real-life experiments and data-driven approach to assess those changes in air quality.

Second, the findings of this research can inform the development of policies and interventions aimed at improving air quality. By identifying the key determinants of air pollution levels, we can develop more targeted and effective strategies for reducing emissions and improving air quality.

5. Results and discussion

5.1. Short-term changes of pollutants' levels within each year

This section evaluates the changes of the three pollutants levels within the year. The evaluation was performed to assess the short-term changes of pollutants' levels, by comparing the pollutant's levels within the same year. The comparison considered the changes from the beginning of the year (i.e., January) and the middle of the year (June), since the seasons are changing from Winter to Summer, and the temperature drops from its lowest to the highest. Fig. 4 shows the changes in June when compared to January of each year.

In particular, the changes in $PM_{2.5}$ concentration between the beginning of the year and the middle of the year. This period was selected since it corresponds to the period where the lockdown period has no effect (i.e., the beginning of 2020) to the period where the lockdown restrictions were at their peak (i.e., the middle of 2020). For

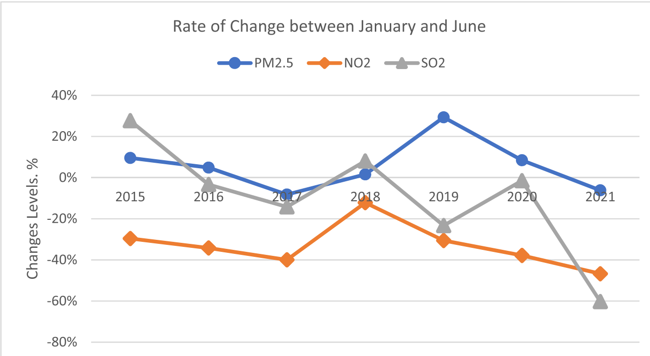

Fig. 4. Rate of Change of Pollutants' Levels between January and June for the years 2015–2021.

consistency, the same period was used to compare the changes for all studied years (2015–2021). It was noticed that the changes during the first six months (i.e., January and June) of each year range mostly between ±9 %, where some years experienced an increase during the first six months of the year, and other years experienced a reduction during the same period. Moreover, there was no specific trend for these changes as well. Most of the years experienced an increase in June when compared to January, except for two years (2017 and 2021).

As for NO_2, and unlike the observed trend for $PM_{2.5}$, the average daily NO_2 concentration was dropped by 29.6 % during the first six months of 2015. The drop percentages during the first six months in 2020 and 2021 were 37.8 % and 46.7 %, respectively. The average reduction during the first six months and across all years was approximately 33.0 %. NO_2 levels in June were lower than those of January for all the years, without an exception.

With respect to SO_2 levels, concentrations levels in June were less than the levels in January for most of the years, except for 2015 and 2018. In 2015 and 2018, the levels in June were higher than those in January by approximately 27.7 % and 8.0 %, respectively. As for the COVID-19 lockdown period in 2020, it was noticed that the differences between SO_2 levels in January and June are marginal. However, the SO_2 levels in June have dropped by almost 60 % when compared to its levels in January in 2021.

5.2. $PM_{2.5}$ Mass concentration

Fig. 5 summarizes the annual average daily levels of $PM_{2.5}$ across all available monitoring stations in the State of Florida. The figure shows that the average $PM_{2.5}$ levels is slightly declining over time. For instance, the annual average daily levels drop by 7.27 % from 8.88 μg/m^3 in 2015 to 8.35 and 8.24 μg/m^3 in 2020 and 2021, respectively. Moreover, the variation of $PM_{2.5}$ levels were also reduced over time, where the annual variance dropped from 8.87 in 2015 to 7.42 and 4.14 in 2020 and 2021, respectively.

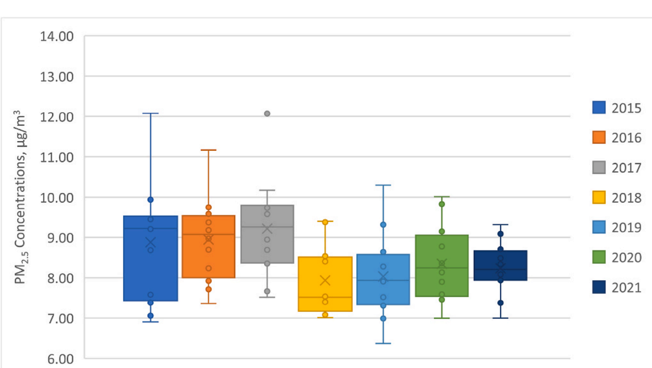

Fig. 5. Boxplot representing Average Daily $PM_{2.5}$ Levels for the years 2015–2021.

Fig. 6 shows the statewide daily average $PM_{2.5}$ concentrations for the years of 2015–2021. There is a trend of descending rates over each year. Furthermore, the width of the regression slope with 95th percentile confidence interval is reduced over time, which indicates less variability over time. This reduction in variability can also be attributed to overall air quality improvement.

A summary of the TLR models for 2020 and 2021 results are shown in Table 2. The first comparison that can be made is related to the intercepts. The results show that the intercepts associated with the year covariates are insignificant at 95th percentile confidence level. This indicates that despite the overall reductions in 2020 and 2021, there was no statistically significant evidence that $PM_{2.5}$ concentrations have changed in 2020 and 2021 when compared to the previous years (i.e., 2015–2019).

With respect to the differences in regression slopes, which is expressed by the interaction between Day and Year covariates, the results of the ANCOVA test shown in Table 3 indicate that there is no statistical evidence that the slopes in 2020 and 2021 are different than those observed in the examined previous years, where the p-value is 0.859. This observation is suggesting that the rate of change in $PM_{2.5}$ concentrations in 2020 and 2021 is similar to the previous years.

Therefore, it is concluded that there is no significant statistical evidence to suggest that the COVID-19 pandemic has attributed to the drop in $PM_{2.5}$ concentrations in 2020 or 2021. On the other hand, this drop can be attributed to other factors that are associated with overall improvement in air quality.

5.3. NO_2 concentration

Fig. 7 summarizes the annual average daily concentrations of NO_2 across all monitoring stations in the State of Florida. The figure does not show specific or distinct average or variance trend across the study years. The width of the 95 % CI of regression slopes were constant over the years indicating no variability. In general, the NO_2 concentrations in any of the studied year were high during the winter months, and they decreased as the middle of the year is approached. The months of June, July, and August have experienced the lowest NO_2 concentrations within the year. However, there was no statistical evidence to suggest that the NO_2 concentrations have improved over the years. Similarly, there is no statistical evidence to suggest that NO_2 concentrations during the pandemic were less than the previous years.

Fig. 8 shows the average dailyNO_2 levels in the years of 2015–2021. In general, there is no conclusive trend for the regression slope over each year. Some years show a descending trend, other years show ascending or no trend. However, the trend for 2021 is ascending, which indicates the presence of activities associated with NO_2 during this year. Nonetheless, further statistical evidence must be presented before a conclusion can be drawn. Furthermore, the width of the 95th percentile confidence interval of the regression slope across the years is almost similar, which is consistent with the variability statement shown in Fig. 7.

The results summarized in Table 4 show that the differences between the time-lag linear regression slopes in 2020 and 2021 are not significant, where the p-value of the ANCOVA test is 0.401. This finding with respect to NO_2 concentrations is consistent with the findings associated with $PM_{2.5}$ concentrations.

As for the NO_2 seasonal variation, other studies have documented that the NO_2 levels during the middle of the year (i.e., the months of the summer) tend to be lower than the beginning and the end of the year (i.e., the months of the winter) in New York, New Jersey, and Portugal [67, 68]. These seasonal variation statements support the findings of this study. While those studies have reported the findings in cities that are having different climate and weather conditions than the ones found in Florida, they are still important findings to verify that changes in NO_2

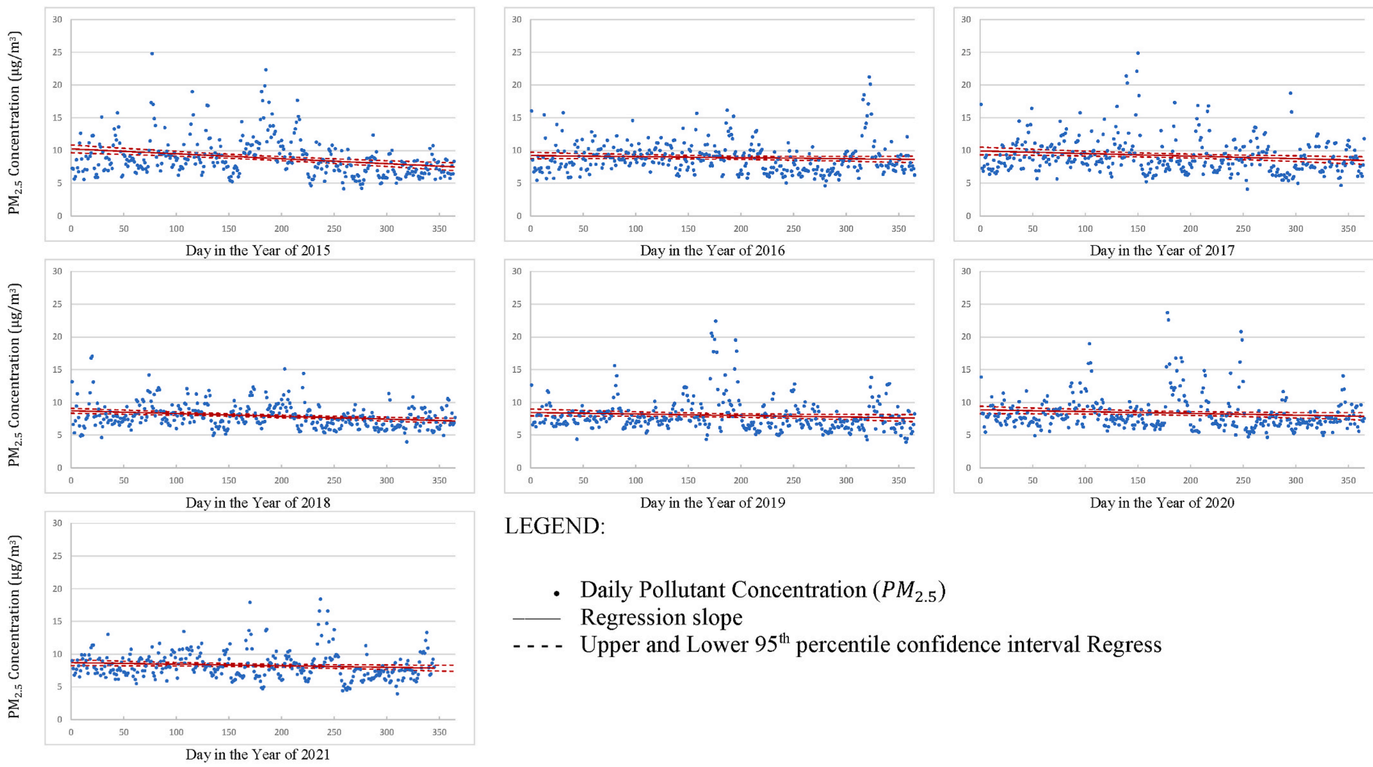

Fig. 6. Daily average mass concentrations of $PM_{2.5}$ in the state of Florida between 2015 and 2022.

Table 2
Coefficient estimates (95 % confidence intervals) of differences in the intercepts from the linear time lag model for 2015–2020 for $PM_{2.5}$, NO_2, and SO_2 concentrations by year compared to 2021 values.

Year	$PM_{2.5}$, ($\mu g/m^3$)		NO_2, (ppb)		SO_2, (ppb)	
	Intercept	95th CI	Intercept	95th CI	Intercept	95th CI
2015	0.429	(-0.017, 0.875)	0.296	(-0.760, 1.353)	2.081[b]	(1.633, 2.528)
2016	0.127	(-0.317, 0.571)	0.370	(-0.686, 1.425)	0.695[b]	(0.260, 1.130)
2017	0.304	(-0.141, 0.749)	0.113	(-0.944, 1.169)	−0.150	(-0.584, 0.284)
2018	−0.045	(-0.489, 0.399)	0.567	(-0.490, 1.625)	0.033	(-0.401, 0.467)
2019	−0.090	(-0.534, 0.354)	0.289	(-0.767, 1.346)	−0.475[a]	(-0.909, −0.040)
2020	0.040	(-0.472, 0.553)	0.060	(-1.157, 1.278)	−0.723[b]	(-1.225, −0.222)

[a] $p < 0.05$.
[b] $p < 0.01$.

levels are not sensitive to the severe changes in weather conditions between summer and winter months. As for studies during the pandemic that are based on Florida, a study reported that significant short-term reduction of air quality for the cities of Jacksonville, Tallahassee, Gainesville, Orlando, Tampa, and Miami during the pandemic [22].

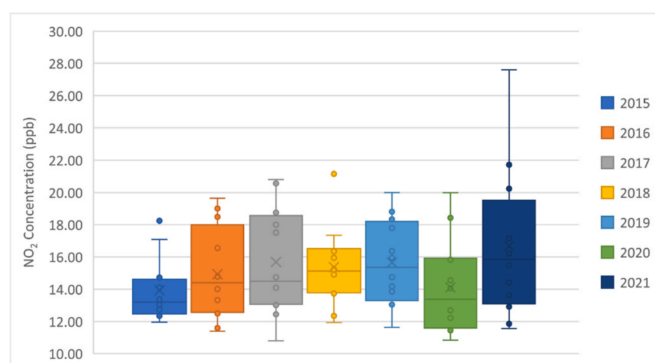

Fig. 7. Boxplot representing Average Daily NO_2 Levels for the years 2015–2021.

Table 3
Results of ANCOVA test for the $PM_{2.5}$ linear time-lag model.

Source	Type III Sum of Squares	Degree of Freedom	Mean Square	F-value	Significance
Dependent Variable: $PM_{2.5}$					
Corrected Model	9144.429	14	653.173	210.095	0.000
Intercept	1009.907	1	1009.907	324.839	0.000
Year Covariate (Intercept)	20.442	6	3.407	1.096	0.362
Day Covariate	26.363	1	26.363	8.480	0.004
Time Lag	8161.390	1	8161.390	2625.133	0.000
Year * Day Interaction (Slope)	8.036	6	1.339	.431	0.859
Error	7902.933	2542	3.109		

$R^2 = 0.536$ (Adjusted $R^2 = 0.534$).

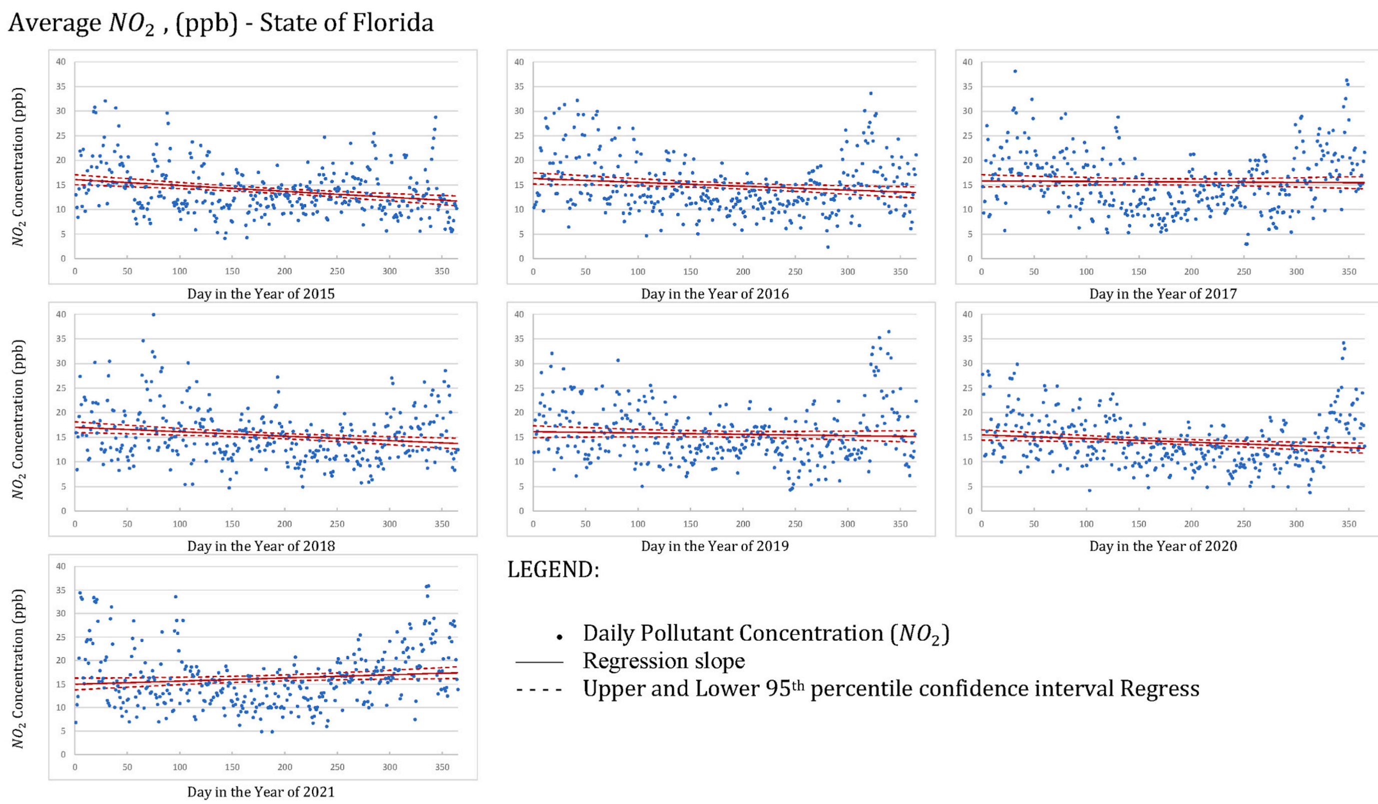

Fig. 8. Daily average mass concentrations of NO_2 in the state of Florida between 2015 and 2022.

Table 4
Results of ANCOVA test for the NO_2 linear time-lag model.

Source	Type III Sum of Squares	Degree of Freedom	Mean Square	F-value	Significance
Dependent Variable: NO_2					
Corrected Model	36738.706	14	2624.193	149.590	0.000
Intercept	6237.417	1	6237.417	355.560	0.000
Year Covariate (Intercept)	24.729	6	4.122	.235	0.965
Day Covariate	69.055	1	69.055	3.936	0.047
Time Lag	33564.176	1	33564.176	1913.302	0.000
Year * Day Interaction (Slope)	108.772	6	18.129	1.033	0.401
Error	44593.128	2542	17.543	–	–

$R^2 = 0.452$ (Adjusted $R^2 = 0.449$).

5.4. SO_2 concentration

The annual average daily concentrations for SO_2 are presented in Fig. 9 for all monitoring stations across State of Florida. Overall, the average yearly concentrations observed a constant decrease was observed from 2015 to 2020 with a sudden increase in 2021. The average SO_2 concentrations reduced from 4.3 ppb in 2015 to 2.0 ppb in 2020 and 2.62 ppb in 2021 observing 53.3 % and 38.8 % reduction, respectively. Furthermore, the variance also showed similar trends with 5.6 ppb in 2015 and 1.6 ppb in 2020 and a higher value (sudden increase) in 2021 of 10.1 ppb.

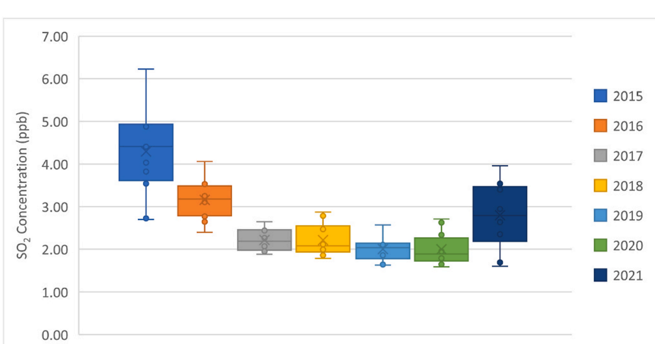

Fig. 9. Boxplot representing Average Daily SO_2 Levels for the years 2015–2021.

Fig. 10 presents the average daily concentrations of SO_2 for each day of the year. Generally, the lower concentrations were observed in the initial months (first quarter) of the year. The 95 % confidence interval of the slopes reduced gradually from 2015 to 2020 showing lesser variation in SO_2 levels. The variance increased significantly for 2021.

The results for TLR model were previously presented in Table 2. The results indicate that the intercept was significant for all years except 2017 and 2018. Table 5 summarized the results of the ANCOVA test for SO_2 levels. The test results show that the significance was less than 0.001 indicating that the SO_2 concentrations changed significantly in 2021 compared to 2015. These findings were contrary to the trends observed for $PM_{2.5}$ and NO_2 levels.

According to the data presented in Fig. 9, the annual average daily concentrations of SO_2 showed a decline from 2015 to 2020, followed by a sudden increase in 2021. This increase was unexpected, considering

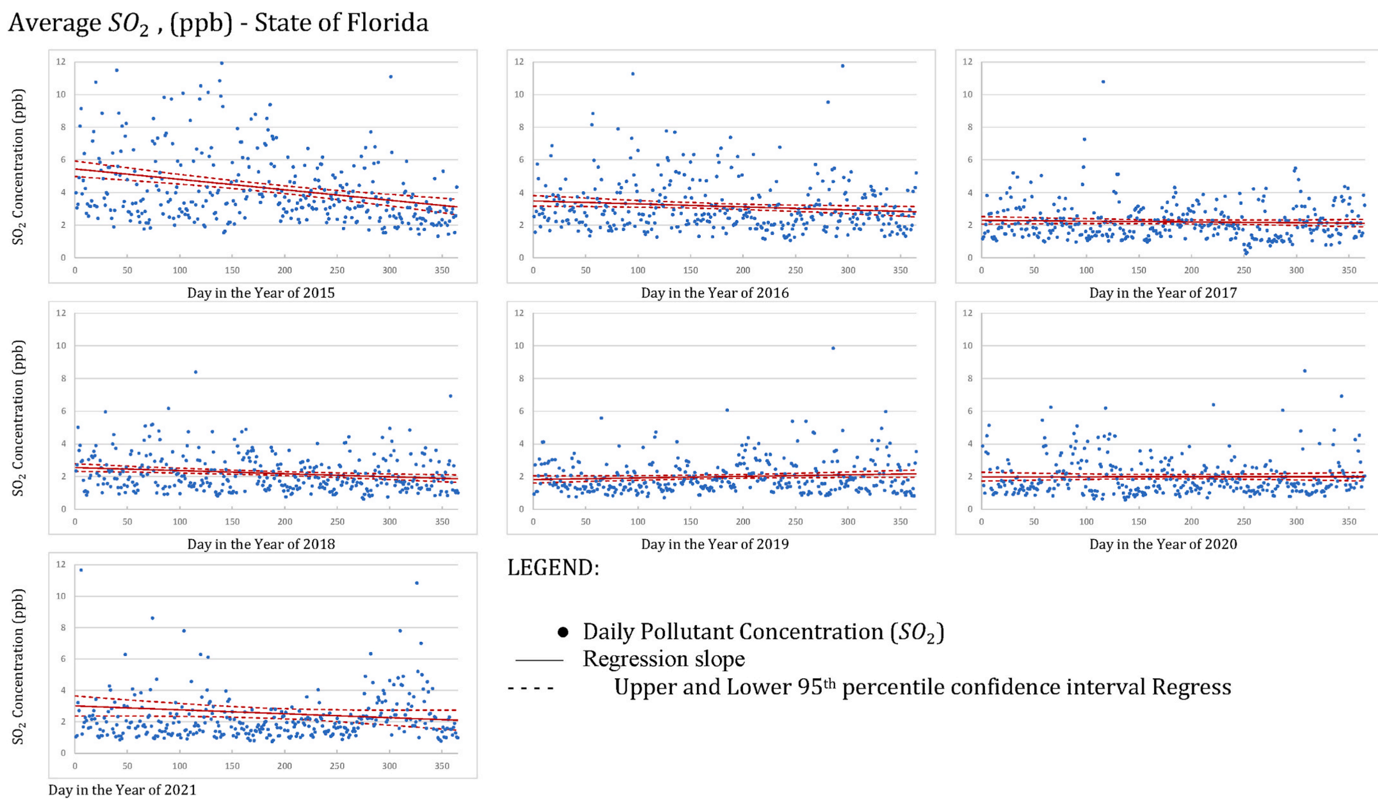

Fig. 10. Daily average mass concentrations of SO_2 in the state of Florida between 2015 and 2022.

Table 5
Results of ANCOVA test for the SO_2 linear time-lag model.

Source	Type III Sum of Squares	Degree of Freedom	Mean Square	F-value	Significance
Dependent Variable: SO_2					
Corrected Model	2433.357	14	173.811	58.731	0.000
Intercept	1663.646	1	1663.646	562.152	0.000
Year Covariate (Intercept)	388.744	6	64.791	21.893	0.000
Day Covariate	41.313	1	41.313	13.960	0.000
Time Lag	688.955	1	688.955	232.800	0.000
Year * Day Interaction (Slope)	69.103	6	11.517	3.892	0.001
Error	7522.859	2542	2.959	–	–

$R^2 = 0.244$ (Adjusted $R^2 = 0.240$).

the relatively restricted transportation activities in 2019. This inconsistency raises questions about whether the transportation sector is the primary contributor to the emission of SO_2 concentrations. It is worth noting that the continuous reduction of coal-fired generation, driven by environmental regulations and the Clean Air Act Amendments (CAAA) of 1990, effectively led to a decrease in both total and electric power industry SO_2 emissions over several decades, up until 2020 [69]. Coal is notorious for its high SO_2 emissions, registering at 3900 pounds per million kilowatt-hours (lb/mil. kWh) in power plants, a clear contrast to more environmentally friendly fossil fuels such as natural gas, which emit only 5 lb/mil. kWh [70].

5.5. Discussion

While the implemented environmental policies and regulations have caused a relatively steady declining trend controlling the sources of $PM_{2.5}$ and NO_2 levels, these policies did not result in a parallel trend for SO_2 levels, which indicates that there is a need to implement further sustainable policies and initiatives targeting the sources of SO_2 levels, such as industrial activities or power generation plants, which emphasizes the role of environmental policies and regulations in achieving environmental benefits.

The results show that the statewide daily average $PM_{2.5}$ levels showed a descending trend over each year, with a narrower confidence interval over time, confirming the reduction in variability and improvement in air quality. The TLR models did not find any significant difference in the intercepts or slopes of $PM_{2.5}$ levels between 2020 and 2021 and the previous years, suggesting that the COVID-19 pandemic did not have a statistically significant effect on the $PM_{2.5}$ levels in Florida.

NO_2 levels consistently decreased during the first six months of each year. The annual average daily levels did not show any specific or distinct trend or variation over time. The levels were higher during the winter months and lower during the summer months for all the years, without exception. The statewide NO_2 daily average levels did not show any conclusive trend over each year. The TLR models did not find any significant difference in the slopes of NO_2 levels between 2020 and 2021 and the previous years, suggesting that the COVID-19 pandemic did not have a statistically significant effect on the NO_2 levels in Florida.

SO_2 levels mostly decreased during the first six months of each year, except for 2015 and 2018. The most notable decrease was observed in 2021, where SO_2 levels dropped by almost 60 %. This indicates that the COVID-19 lockdown may have reduced SO_2 emissions from industrial and power generation activities.

The TLR models found that the intercept was significant for all years except 2017 and 2018, suggesting that there was a change in SO_2 levels between those years and the other years. The ANCOVA test found that there was a significant difference in the slopes of SO_2 levels between 2021 and 2015, suggesting that the COVID-19 pandemic had a statistically significant effect on increasing the SO_2 levels in Florida. This finding was contrary to the findings for $PM_{2.5}$ and NO_2 levels, which did not show any significant effect of the pandemic.

In summary, the results reveal that the $PM_{2.5}$ and NO_2 levels during the pandemic are not statistically different than the long-term historical trends of these two pollutants. Furthermore, the SO_2 the pandemic has a short-term impact on SO_2 levels. Where these levels during the pandemic were different that the long-term historical trend.

The absence of a significant correlation between the concentrations of $PM_{2.5}$, NO_x, and SO_2 and transportation activities suggests that transportation alone cannot account for the variation in air pollutant levels. Other sectors contributing to air pollution, such as power plants, may exert a more noticeable influence on air quality. This is supported by the observed similarity between trends in coal consumption in power plants and average annual pollution levels.

6. Conclusions and recommendations

The COVD-19 pandemic forced many governmental and official entities from all over the world to impose certain measures to suppress the spread of the pandemic. Those measures have changed many daily socioeconomic activities. While some of those activities were reduced, such as motorized mobility, other activities have experienced a substantial increase, such as the increase in generated power demand. Therefore, the changes in such socioeconomic activities were attributed to changes in air quality. Several studies have assessed the short-term impacts of the changes in activities on the air quality. However, the long-term significance of these changes did not drag the same attention, creating the need to assess and investigate the long-term impact of COVID-19 on air quality as well. This paper investigates the statewide short-term and long-term impacts of COVID-19 pandemic on the State of Florida. The study investigates three air quality indicators that are highly influenced by the changes in socioeconomic activities, fine particulate matters ($PM_{2.5}$), nitrogen dioxide (NO_2), and sulfur dioxide (SO_2). The study period covers three main periods, pre-pandemic period between 2015 and 2019, lockdown in 2020, and post-pandemic in 2021.

The results have revealed that the short-term changes for $PM_{2.5}$ and NO_2 levels during the three study periods were not statistically significant. Likewise, the long-term changes were not significant as well, as there was a declining trend in the levels of those two pollutants, which can be attributed to other factors, such as environmental regulations and vehicular emissions' pollutants. In particular, the changes in regression slopes and the intercepts of pollutants' levels were insignificant.

However, the changes in SO_2 levels have a taken a different path. As there was no clear and distinct historical trend, the short-term changes of SO_2 levels in 2020 and 2021 were statistically significant when compared to the pre-pandemic period. This observation is consistent with the observed increase demand of generated power [22]. When the long-term changes of SO_2 levels are considered, the same conclusion can be drawn, where the changes in SO_2 levels in 2020 and 2021 were not influenced by the historical change in SO_2 levels. The study also found that lockdown measures led to a reduction in industrial activity, which is reflected in the decline in SO_2 levels. This suggests that reducing industrial emissions may be a particularly effective way to improve air quality.

Overall, this research has the potential to make a significant contribution to improving public health and well-being by helping us to reduce exposure to air pollution. Although this study gives a statewide assessment of air quality in the State of Florida, it has some limitations that should be further investigated.

The study did not account for all potential factors that may have influenced air quality levels during the pandemic, such as changes in weather patterns, transportation demand, or economic activity. For instance, this study should be further expanded to assess and evaluate the contribution of several socioeconomic and demographic factors, such as vehicular demand, land use, meteorology, and population factors on changes in different air quality index.

The study was conducted in a single state (Florida), so the findings may not be generalizable to other parts of the United States or the world. Within this context, it is recommended to compare air quality within different areas in the same state, such as metropolitan and nonmetropolitan areas, or urban, suburban, and rural areas, where impact of changes in socio-economic activities on air quality could potentially be different. These recommended studies would tremendously benefit from the large-scale and global social experiment opportunities that were introduced by the COVID-19 pandemic, and the response measures that came along. Moreover, it is important to note that this research did not encompass the examination of the location and extent of coal consumption by power plants in the studied areas. Investigating the impact of these factors can potentially provide valuable insights and is recommended for future research. This study was also limited to three pollutants, and it is recommended in future research to consider other pollutants, such as Ozone and Carbon Monoxide.

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.

Data availability

Data will be made available on request.

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