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The impact of stay-at-home orders on air-quality and COVID-19 mortality rate in the United States

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ABSTRACT

Since the beginning of the pandemic in the U.S., most jurisdictions issued mitigation strategies, such as restricting businesses and population movements. This provided an opportunity to measure any positive implications on air quality and COVID-19 mortality rate during a time of limited social interactions. Four broad categories of stay-at-home orders (for states following the order for at least 40 days, for states with less than 40 days, for states with the advisory order, and the states with no stay-at-home order) were created to analyze change in air quality and mortality rate. Ground-based monitoring data for particulate matter ($PM_{2.5}$, PM_{10}), nitrogen dioxide (NO_2), sulfur dioxide (SO_2) and carbon monoxide (CO) was collected during the initial country-wide lockdown period (15 March-15 June 2020). Data on confirmed COVID-19 cases and deaths were also collected to analyze the effects of the four measures on the mortality trend. Findings show air quality improvement for the states staying under lockdown longer compared to states without a stay-at-home order. All stay-at-home order categories, except states without measures were observed a decrease in $PM_{2.5}$ and the core-based statistical areas (CBSAs) within the longer mitigation states had an improvement of their air quality index (AQI).

1. Introduction

Exposure to long-term air pollution is a well-known reason behind numerous adverse lung-diseases, emergency visits, and frequent hospital visits (Szyszkowicz et al., 2018; Zhang et al., 2018). Around 91% of the global population are exposed to air pollution annually, causing 4.2 million deaths attributable to poor air quality (WHO, 2020). Air pollution alone can affect life expectancy more than twice the combined effects of soil, water, and other occupational pollution (Moelling and Broecker, 2020). Particulate matters with a diameter smaller than 2.5 μm ($PM_{2.5}$) and 10 μm (PM_{10}), sulfur dioxide (SO_2), nitrogen dioxide (NO_2), and carbon monoxide (C.O.), are the most common pollutants included in the list of five 'criteria' air pollutants, which are generated from a wide range of emission sources (Suh et al., 2000). Due to the smaller diameter, $PM_{2.5}$ can inflict damage by carrying other toxic contents and penetrating deep into the lungs and bloodstreams, while PM_{10} particles were also associated with respiratory diseases (Xing et al., 2016). Long-term exposure to nitrogen dioxide (NO_2) can induce infections of the lower respiratory tract and can increase airway responsiveness in asthma patients (Folinsbee, 1993). Sulfur dioxide (SO_2) is one of the most widespread air pollutants in the

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industrialized era which is mostly emitted by the coal-fired power plants, smelters, and ports, can cause reduced lung functionality from its chronic exposure. Carbon monoxide (CO), mainly emitted by incomplete combustions in the gasoline-vehicles, reduce the oxygen-carrying capacity of the blood and create imminent risk for the vulnerable, including children, the elderly, anemics, diabetics, people with heart diseases, and people with chronic obstructive pulmonary disease (EPA, 2015). SO_2-induced respiratory illnesses increase emergency visits and hospital admissions among the vulnerable population.

The novel coronavirus disease (COVID-19), the most recent global pandemic, has claimed over 2.2 million deaths worldwide by the end of January 2021 (Ritchie et al., 2021). Many parts of the world went through lockdowns as a primary strategy to protect public health. The U.S. and its territories implemented several stay-at-home order policies since March 2020 to limit community interactions and prevent the transmission through the adoption of social and physical distancing. Since each state has authority to legislate its own policies, the extent and nature of the community mitigation policies varied from one state to another. Nevertheless, these mobility restrictions resulted in an improved traffic-related air quality across the states, with similar findings observed in cities around the world that followed certain levels of community mitigation strategies (Lian et al., 2020; Shi and Brasseur, 2020; Naqvi et al., 2021; Kerimray et al., 2020; Nakada and Urban, 2020; Stratoulias and Nuthammachot, 2020). These containment measures, including travel restrictions have altered people's way of performing office work, participating in social events, mode of education, and reduced usual traffic footprint, manufacturing, and industrial activities. These changes in daily life have significantly reduced environmental pollution by lowering the concentrations of ambient air pollutants. Shakoor et al. (2020) found 1.1% $PM_{2.5}$, 37% NO_2, 19% CO reduction in the U.S. and 18% $PM_{2.5}$, 18% SO_2, 39% NO_2, 27% CO drop by concentration in China when comparing before and after lockdowns. Significant drops in NO_2 emissions were observed worldwide by the National Aeronautics and Space Administration (NASA) and European Space Agency (ESA) air pollution satellites (ESA, 2020; NASA, 2020; Zhang et al., 2020). The drastic decrease in air pollutants was visible only after the 4th day of lockdown in 88 cities of India (Mahato et al., 2020; Sharma et al., 2020; Srivastava et al., 2020; Singh and Chauhan, 2020).

Populations with comorbidities, such as respiratory and cardiovascular diseases as well as diabetes, are at higher risk to suffer from both air pollution (Qiu et al., 2015) and the COVID-19 virus during this pandemic (Chen et al., 2020; Maddox et al., 2020; Wang et al., 2020; Wu et al., 2020; Zhu et al., 2020). Researchera also associated a higher risk of mortality from COVID-19 infections with high levels of poor air quality (Yongjian et al., 2020; Conticini et al., 2020). Thus, the social containment strategies implemented to minimize COVID-19 transmission and mortalities have indirectly benefitted the environment and our health by improving air quality. Most studies have reported air quality improvement specific to different cities in the U.S. and Worldwide. However, the implications of different stay-at-home orders on reducing air pollution and the rate of COVID-19 mortality in the U.S. have not been explored. Therefore, this study aims to add to our findings regarding the extent of quality improvement for five criteria air pollutants ($PM_{2.5}$, PM_{10}, SO_2, NO_2, CO) in terms of four different categories of stay-at-home orders and their potential effects on lowering the trend of the COVID-19 mortality rate within the domain of the conterminous U.S. containing 48 states and District of Columbia.

2. Methodology

2.1. Stay-at-home order categories and the study domain

In the U.S., 42 states and territories began executing various mitigation policies to prevent person-to-person COVID-19 transmission by controlling population interactions within the community. To assess the implications of stay-at-home orders on the air quality level and understand any effects on mortality, we first studied how each state implemented its statewide order and how long those orders have been in place. The mandatory stay-at home orders were initially issued by 42 states and territories between March 1st to May 31st. Among those, 12 jurisdictions permitted the home orders to expire their orders, and mandatory orders were transitioned to an advisory by 22 states. The remaining eight states extended their mandatory orders beyond the 31st of May. In addition, eight states issued advisory orders by recommending residents to stay at home, and six states did not mandate any order at all during the three months (Moreland et al., 2020). However, few states issued state-wide orders late in April 2020. Hence, to observe the type and length of these safety orders for the contiguous U.S. in an extended timeline, we selected (15 March-15 June 2020) as our study period to assess the air quality scenarios for different stay-at-home order types. Although various types of restrictions are still in place for the states as of June 2021, we focused on the early stage of COVID-19 in the U.S. During this period, different states had clear mandates about social distancing and stay at home orders, therefore, the effect on air quality would be pronounced for that timeline. The majority of the jurisdictions issued multiple orders in combination which varied in the length and type of the orders. We observed

Table 1
Corresponding stay-at-home order categories and respective implementing states in the contiguous U.S. from March 1st to June 30st, 2020.

Stay-at-home order categories	Implementing states
Stay-at-home order for all or people at increased risk implemented for at least 40 days	Arizona, California, Connecticut, Delaware, District of Columbia, Illinois, Louisiana, Maine, Maryland, Michigan, Minnesota, New Hampshire, New Jersey, New York, North Carolina, Ohio, Oklahoma, Oregon, Pennsylvania, Rhode Island, Vermont, Virginia, Washington, West Virginia, Wisconsin (Total: 25 states)
Stay-at-home order issued for less than 40 days or later continued as advisory order or followed a less strict approach	Alabama, Colorado, Florida, Georgia, Idaho, Indiana, Kansas, Mississippi, Missouri, Montana, Nevada, South Carolina, Tennessee (Total: 13 states)
Advisory order only	Kentucky, Massachusetts, New Mexico, Texas, Utah (Total: 5 states)
No stay-at-home order	Arkansas, Iowa, Nebraska, North Dakota, South Dakota, Wyoming (Total: 6 states)

the extension, expiration, duration of stay-at-home orders, and transition to advisory orders for 49 jurisdictions in the contiguous U.S. during March 15th to June 15th. Upon studying the administrative or executive orders from the different state government, 48 states and District of Columbia were categorized into four mutually exclusive groups: states following the stay-at-home orders for all or people at increased risk for at least 40 days, states that issued stay-at-home order for less than 40 days or later continued as advisory order or less strict approach, states following advisory orders only, and states which did not issue stay-at-home orders at all. State executive orders have been issued by the state governors in response to protecting public health, while administrative orders are delegations of any administration or authority for specific functions.

Table 1 shows a list of 49 jurisdictions (including District of Columbia) within the domain of Contiguous U.S. grouped into four categories above of public health measures. 6 states out of 49 were identified as states with 'No stay-at-home order' from our observation through the study period, 5 states followed advisory order without transitioning to other order type, 25 states maintained stay-at-home orders for at least 40 days, and 49–6–5-25 = 13 states followed stay-at-home order for less than 40 days or later transitioned to other order types.

2.2. Air quality parameters and their study period

The air quality parameters selected for this study are five criteria air pollutants: particulate matter ($PM_{2.5}$, PM_{10}), SO_2, NO_2, and CO. The concentrations of these critical pollutants are regularly monitored, collected, and uploaded to be publicly available by AirData or AQS, the online Air quality System of the U.S. Environmental Protection Agency (USEPA). In addition, based on the past COVID-19 studies from 2020, these five pollutants were observed to significantly reduce during the COVID-19 lockdown period (Archer et al., 2020), which was one reason to be included and studied thoroughly.

The majority of the states implemented mitigation measures from March to May of 2020. California was the first state within the contiguous U.S. to issue a mandatory stay-at-home order on March 19th, while Iowa was the last state to mandate an advisory order on April 27th, 2020. Since a few jurisdictions acted late in the first and last week of April, we intended to observe all states until mid-June 2020. Therefore, we selected a three-month baseline period starting from March 19th to June 15th of 2020 as our observation period. A comparative analysis of air quality is required between pre-lockdown data and lock down data to correctly measure and statistically prove the significance in air quality improvement. Hence, to provide a robust conclusion on any change in air quality in 2020, we chose the same three months from 2015 to 2019 as a pre-lockdown condition to represent the period of usual uninterrupted human activities and low seasonal variability.

2.3. Data collection

The data for the five criteria air pollutants, including lockdown and pre-lockdown historical data, have been collected from the pre-generated data files provided by the EPA air quality system (US EPA, 2020). These data are collected from monitoring sites across the country and aggregated into daily and annual summaries and made available to the public as pre-generated files in 'csv' format. For our analysis, we have used data in the format of daily summaries, which provide daily average concentrations for each monitor per day, aggregated from the sub-daily measurements if more than one sample is collected per day. $PM_{2.5}$ and PM_{10} concentrations are measured by drawing air samples through monitoring filters for 24 h and averaging them. For NO_2 and SO_2, the samples are collected for 1 h to be aggregated into daily values. CO daily values are averaged from the data collected for 8 h.

One of our goals was to observe possible pollutant reduction within the core urban areas due to the limited traffic and population movements during the lockdown. Hence, we also analyzed the pollutants within the Core-based statistical areas (CBSAs) of the United States. CBSAs are characterized by one or more counties or equivalent entities that consist of at least one urban cluster or urbanized area, resided by at least a population of 10,000 having high commuting connections with its core. In addition, we collected EPA pre-generated daily air quality index (AQI) data aggregated by the CBSA jurisdictions within the contiguous U.S. (US EPA, 2020). Since AQI values for most CBSAs were calculated for $PM_{2.5}$ and most CBSAs were missing AQI values for other criteria pollutants, we considered studying $PM_{2.5}$ AQI values for studying CBSA regions.

We used the most recent data on the aggregate counts of COVID-19 cases and deaths for each state to study the implications of initial statewide stay-at-home order categories on the mortality rate. The data is provided by the Centers for Disease Control of Prevention (CDC) by regularly monitoring the COVID-19 infections, hospitalizations, and death count from different jurisdictions (CDC, 2021). The data includes both probable and confirmed cases and deaths of COVID-19. However, only confirmed daily cases and death counts had been utilized to estimate the infection and death rate over state population. Simultaneously, we also calculated death rate as a percentage of COVID-19 infection cases [(confirmed death counts/infection counts) * 100].

2.4. Analysis steps

The goal of this article is to study of the improvement of air quality in terms of the jurisdictions categorized by the type and strictness of stay-at-home orders. Before estimating the possible reduction in the selected air pollutants during the time of country-wide COVID-19 mitigation measures, we first checked if the pollutant levels in 2020 are statistically different in each category of the stay-at-home orders. Then we compared any change in air pollutants during the months of stay-at-home order with the previous five years. The following steps would be described in the result section: 1) Inferential statistic with *t*-tests to determine the significant difference in the air pollutants between the pre and post COVID-19 lockdown period; 2) Inferential t-tests to determine the significant differences between the air pollutants level of four stay-at-home order categories during COVID-19 lockdown; 3) Estimate changes in AQI values of the CBSA regions during the lockdown period and aggregate the rate of changes by the order categories; and 4) Understand the implications of four stay-at-home order categories on the COVID-19 death rate during the entire year of 2020.

3. Results

We conducted a pair-wise inferential *t*-test between six possible pairs of the order categories and assessed the average concentration of the five air pollutants in the four stay-at-home order jurisdictions followed by the determination of the maximum reduction in pollutants. Table 2 shows 95% confidence intervals of the difference in pollutants' concentration for each pair of order category and their statistical significance level ($p = 0.05$) by the (*) symbol. The four order categories: stay-at-home order for all or people at increased risk implemented for at least 40 days (SO40), stay-at-home order issued for less than 40 days or later continued as advisory order or followed less strict approach (SO40M), advisory order (A.O.), and no stay-at-home order (NSO) have been listed in the table in their short forms, respectively. The table shows significant difference in the level of $PM_{2.5}$, PM_{10}, SO_2, NO_2, and CO between all six pairs, which indicates the viability of comparing these four broad and aggregated jurisdictions. In general, the highest $PM_{2.5}$ concentrations were observed in A.O. states followed by the SO40M, SO40, and NSO states. For PM_{10}, its highest concentration in A.O. states were followed by SO40, SO40M and NSO states. The highest level of NO_2 was found in the order of SO40, SO40M, A.O. and NSO states. Hence, $PM_{2.5}$, PM_{10} and NO_2 were already in the lowest concentration in the NSO states. And the average most SO_2 and CO concentrations were found in the SO40M states followed by the SO40, NSO and A.O. states.

The importance of this study lies in the understanding of how the level of improved air quality is affected by the type and duration of the COVID-19 mitigation measures. Hence, we compared the pollutant concentrations between the historical period and the issuing period of first countrywide stay-at-home orders in 2020 using the Welch *t*-test which does not require the same variance in the two groups of samples. The historical pollutant concentrations were averaged over the period of mid-March to mid-June for the past five years (2015–2019). Table 3 provides 95% confidence interval values of the five pollutants' concentration change in 2020 from the historic period and marks the statistically significant ($p = 0.05$) changes with a (*) symbol. The values indicate that all five pollutants significantly decreased in the SO40 states. $PM_{2.5}$, NO_2 and CO had significant reductions in the SO40M states compared to all historic years. The reduction in the PM_{10} levels was significant compared to all historic years except 2015 and 2016 for SO_2. SO_2, NO_2 and CO levels in the lockdown period also reduced substantially in A.O. states compared to all historic years, but changes in $PM_{2.5}$, SO_2, NO_2 and CO in the NSO states were found insignificant.

Now since we know how pollutants statistically decreased within the boundaries of four order categories, we can determine if there is any statistically significant relationship between the stay-at-home order categories and the decrease in air pollutants by performing the Chi-square test of independence. Since the test only applies to the categorical variables, we categorized all concentration values into two categories: 'yes' and 'no'. The 'yes' data points mean that the pollutants decreased during lockdown months compared to the 2015–2019 average values, the 'no' data points indicate increasing air pollutants in the 2020 study periods. Fig. 1 shows mosaic plots for five air pollutants which are created using a contingency table based on the conditional probabilities, where p values <0.05 represent the statistically significant relationship between pollutant and stay-at-home order categories. The absolute value and signs of the Pearson standard deviations shown for each plot is a measure of the strength and direction in the association between order categories and improved air quality. The figure shows that the stay-at-home order types are statistically associated with the decrease in pollutants for $PM_{2.5}$, PM_{10}, NO_2 and SO_2 but not CO This indicates that the type and length of home orders can determine if the $PM_{2.5}$, PM_{10}, NO_2 and SO_2 pollutants will decrease during the period of home-orders. However, the majority of the boxes in white show less significant departure from the independence due to their standardized residuals within the range [−2,2]. The blue boxes indicate more observations deviating from the expected frequency under the null hypothesis of independence, which represent a more significant association. For example, A.O. states are confidently expected not to decrease in $PM_{2.5}$ and NO_2. Similarly, NSO states are confidently expected to increase in SO_2. However, the two red boxes of SO40 states show less confidence in increasing NO_2 and SO_2 during the lockdown period due to having fewer observations compared to the expected frequencies under the null hypothesis of independence. The height and width of the boxes in the figure are proportional to the percentage of two pollutant categories and four order categories, respectively. Most data points in SO40 states decreased in $PM_{2.5}$ and NO_2 in the lockdown period followed by the SO40M, NSO and A.O. states. Very few data points in all order categories reduced in PM_{10} which means that the sources of PM_{10} emissions significantly increased during the home-orders period. However, the highest frequency of declining PM_{10} was located in the SO40 states.

We intended to compare the current pollutant concentrations collected from the monitoring stations with the historical pollutant levels by using scatterplots. Fig. 2 shows the year 2020 $PM_{2.5}$, PM_{10}, SO_2, NO_2 and CO concentrations (in the y-axis) over their average concentrations during the previous years (2015–2019) (in the x-axis) for all monitoring stations segregated into four stay-at-home

Table 2
95% confidence interval of the difference in pollutants' concentration for each pair of order category.

Pair of order categories	$PM_{2.5}$ (μg/m^3)	PM_{10} (μg/m^3)	SO_2 (ppb)	NO_2 (ppb)	CO (ppm)
SO40 – SO40M	−0.69, −0.54*	1.96, 2.67*	0.16, 0.47*	0.16, 0.47*	−0.01, −0.001*
SO40 – AO	−0.92, −0.72*	−11.12, −7.998*	1.54, 1.75*	1.54, 1.75*	0.04, 0.06*
SO40 – NSO	1.27, 1.5*	5.09, 6.12*	3.93, 4.12*	3.93, 4.12*	0.02, 0.04*
SO40M – AO	−0.32, −0.096*	−13.42, −10.32*	1.17, 1.49*	1.17, 1.49*	0.05, 0.07*
SO40M – NSO	1.87, 2.12*	2.81, 3.78*	3.57, 3.86*	3.57, 3.86*	0.02, 0.04*
AO – NSO	2.06, 2.34*	13.57, 16.76*	2.28, 2.48*	2.28, 2.48*	−0.04, −0.014*

Table 3
Change in $PM_{2.5}$, PM_{10}, SO_2, NO_2 and CO concentration between 2020 and historical years (2015–2019).

Pollutants	Order Categories	2019	2018	2017	2016	2015
$PM_{2.5}$	SO40	−0.52, −0.41*	−1.28, −1.15*	−0.62, −0.49*	−1.08, −0.95*	−1.55, −1.41*
(μg/m^3)	SO40M	−0.45, −0.26*	−0.74, −0.54*	0.19, 0.38*	0.27, 0.50*	−0.56, −0.31*
	AO	−0.03, 0.23	−0.65, −0.37*	1.21, 1.52*	0.87, 1.21*	−0.13, 0.23
	NSO	−0.22, 0.09	−0.66, −0.34*	−0.3, −0.02*	0.24, 0.62*	−0.32, 0.03
PM_{10}	SO40	−2.93, −1.62*	−8.13, −7.13*	−6.43, −4.97*	−6.65, −5.16*	−4.83, −3.43*
(μg/m^3)	SO40M	−0.9, −0.24*	−2.3, −1.63*	−0.82, −0.11*	−0.34, 0.32	−1.67, −0.96*
	AO	0.02, 5.4*	−7.65, −2.56*	−12.15, 1.97	−5.47, −0.39*	4.53, 8.0*
	NSO	0.99, 2.19*	−2.68, −1.32*	−1.8, −0.52*	−1.61, −0.27*	−3.71, −2.25*
SO_2	SO40	−0.08. -0.03*	−0.79, −0.60*	−0.6, −0.48*	−0.57, −0.46*	−0.71, −0.62*
(ppb)	SO40M	−0.69, −0.24*	0.29, 0.52*	0.15, 0.39*	0.16, 0.39*	−0.11, 0.13
	AO	−0.18, −0.01*	−0.36, −0.16*	−0.33, −0.12*	0.07, 0.19*	0.08, 0.21*
	NSO	−0.07, 0.02	−0.09, 0.00	−0.17, −0.06*	−0.22, −0.11*	−0.45, −0.31*
NO_2	SO40	−1.76, −1.54*	−1.98, −1.75*	−1.83, −1.59*	−2.03, −1.79*	−2.14, −1.91*
(ppb)	SO40M	−1.66, −1.23*	−2.41, −1.96*	−1.55, −1.12*	−1.69, −1.25*	−1.39, −0.96*
	AO	−1.02, −0.76*	−1.2, −0.93*	−0.73, −0.46*	−1.16, −0.88*	−1.39 -1.1*
	NSO	−0.32, −0.13*	−0.83 -0.63*	−0.8, −0.6*	−0.67, −0.47*	−1.07, −0.85*
CO	SO40	−0.03, −0.02*	−0.04, −0.03*	−0.03, −0.02*	−0.03, −0.02*	−0.04 -0.03*
(ppm)	SO40M	−0.04, −0.02*	−0.04, −0.03*	−0.05, −0.04*	−0.06, −0.05*	−0.07, −0.05*
	AO	−0.05, −0.03*	−0.1, −0.07*	−0.09, −0.08*	−0.09, −0.07*	−0.04, −0.03*
	NSO	−0.02, 0.0	−0.01, 0.0	−0.04, −0.02*	−0.02, 0.00	−0.004, 0.02

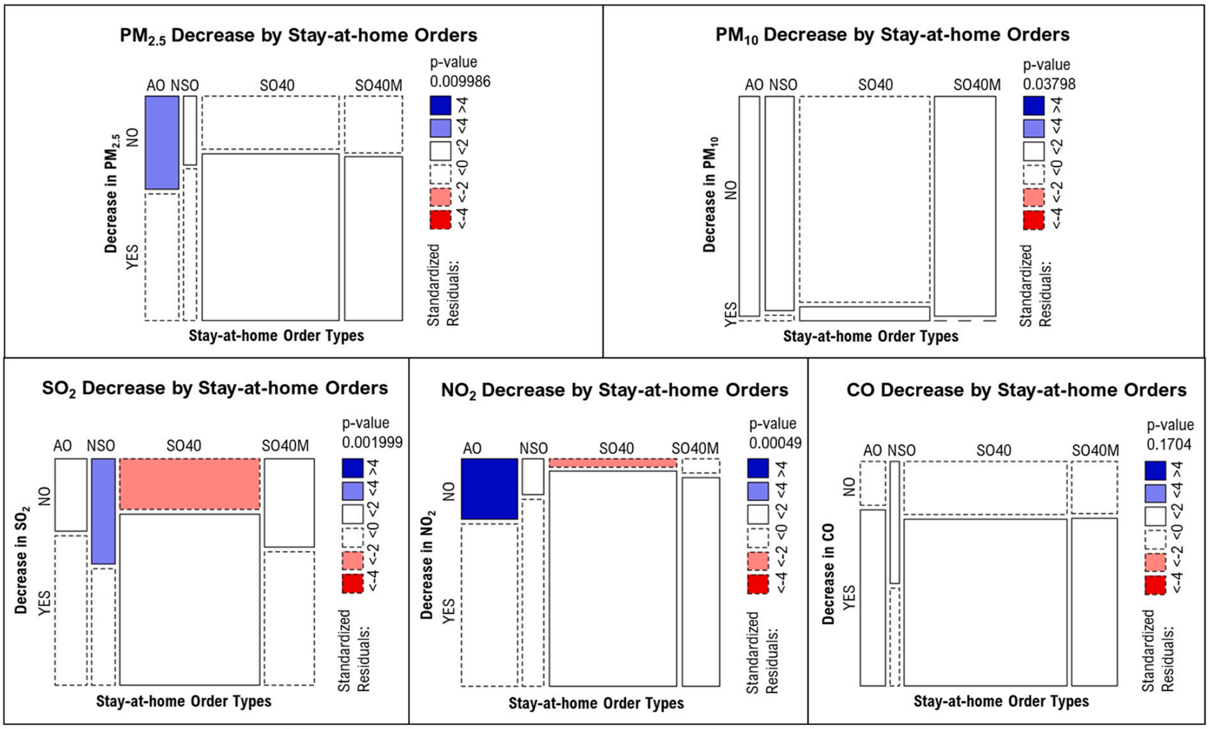

Fig. 1. Results of chi-square test between concentration decrease and 4 stay-at-home order categories. The 'yes' data points mean that the pollutants decreased during lockdown months compared to the 2015–2019 average values, the 'no' data points mean the increased pollutants.

categories (SO40, SO40M, A.O., and NSO). The orange lines represent the ideal 1:1 line, where current pollutant concentrations have no difference with the historical levels. The points falling below the 1:1 line show the monitors improving in air quality during the COVID-19 lockdown, while the points above the line experienced an increase in air pollutants concentrations. The measurements of the $PM_{2.5}$ monitors show that 83.05%, 78.23%, 72.41% and 78.13% of them had $PM_{2.5}$ reduction in the SO40, SO40M, A.O. and ASO states, respectively. The 77.04%, 60%, 67.24%, 52.38% of the SO_2 monitors; and 96.33%, 93.75%, 72.63%, 83.78% of the NO_2 monitors; observed a decline in concentrations within the jurisdictions of four stay-at-home orders, respectively. The figure shows that the highest reduction in the concentrations of $PM_{2.5}$, PM_{10}, SO_2, and NO_2 were detected for the states following longer stay-at-home order. However, 75.76%, 76.09%, 80%, 44.44% of the CO monitors; and 6.36%, 0%, 0%, 2.56% of the PM_{10} monitors had reduction in

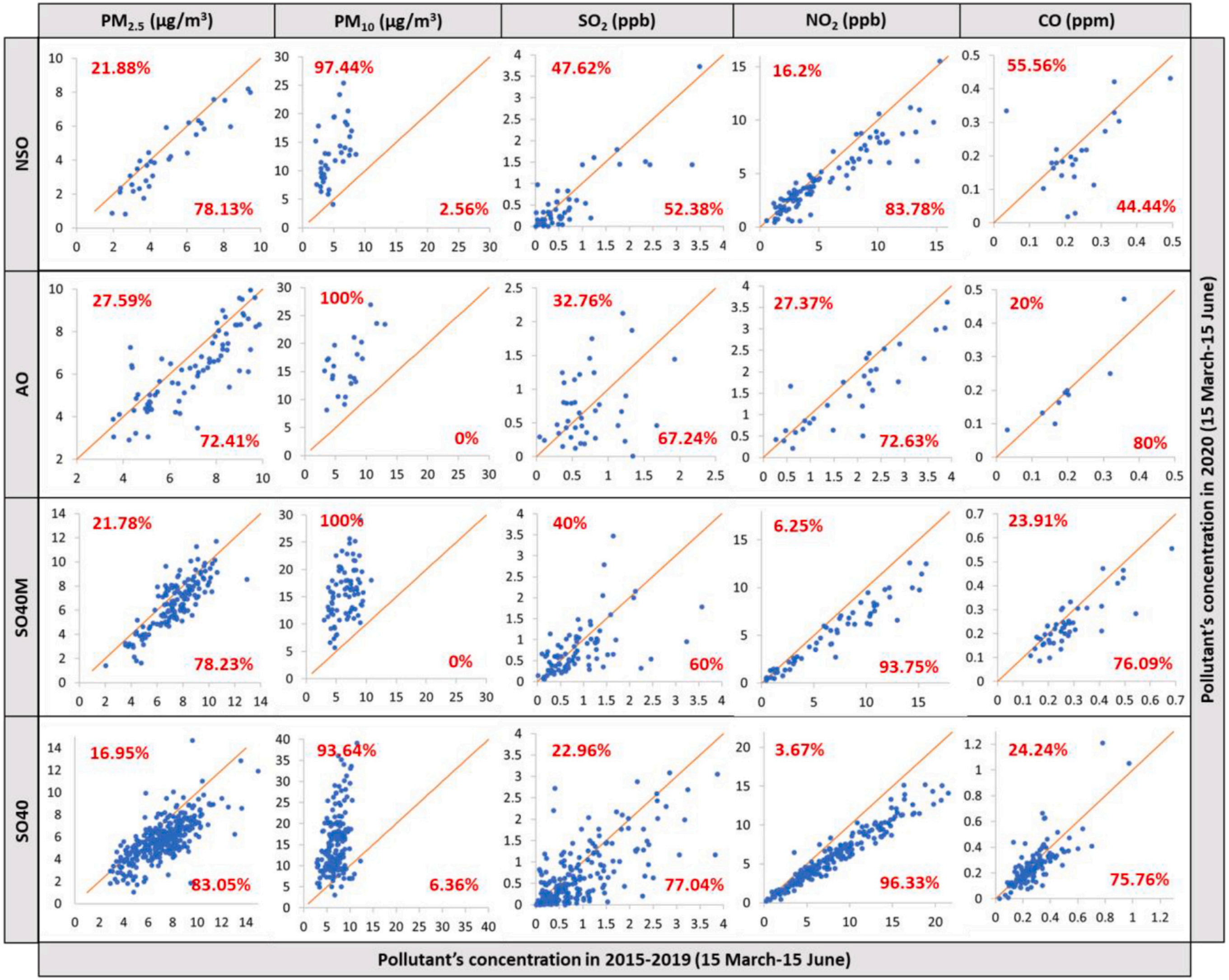

Fig. 2. $PM_{2.5}$, PM_{10}, SO_2, NO_2, and CO concentration of the monitoring stations during the study period of 2020 (in the y-axis) over historical periods (in the x-axis) categorized by four stay-at-home orders.

the respective four categories compared to historical levels, which seems to be unaffected by the length and type of the stay-at-home order. Although highest number (6.36%) of the PM_{10} monitors in SO40 states showed improvement in PM_{10} concentrations, the trend of PM_{10} reduction does not seem to correlate with the stay-at-home order categories.

Further insights on the spatial variability were achieved by mapping the ground monitoring stations for the five pollutants in terms of their decrease in concentrations and locations within the broad boundaries of four stay-at-home order categories. Fig. 3 depicts the average difference of $PM_{2.5}$, PM_{10}, SO_2, NO_2, and CO concentrations between March and June of 2020 and the pre-COVID years (2015–2019), shown by the location points of their monitoring stations. The $PM_{2.5}$ map shows a maximum reduction of 7.3 μg/m^3 and a maximum increase of 5.14 μg/m^3. Most stations with $PM_{2.5}$ drops are located within the SO40 boundary, indicating the states following stay-at-home orders for at least 40 days. The next highest $PM_{2.5}$ reduction stations are situated in the SO40M boundary, followed by the A.O. and NSO regions. The stations with reductions of PM_{10} in 2020 are mostly located in the SO40 regions, followed by only one station in the NSO region. One station in California had a maximum decrease in PM_{10} of about 3.68 μg/m^3. During the lockdown, NO_2 levels in the U.S. had a maximum reduction of 7.53 ppb and a maximum increase of 2.98 ppb. Most of the declines were observed in the SO40 states, followed by the SO40M states. The figure shows similar patterns with a noticeable decrease in SO_2 and CO for the stations within the contiguous United States. SO_2 and CO were observed with the highest drop of 4.8 ppb in North Carolina and 0.296 ppm in California.

After mapping the station-wise reductions, we attempted to aggregate the overall percentage decrease in pollutants by the four broad COVID-19 mitigation strategies. Fig. 4 depicts the percent decrease in the concentration of air pollutants during the 2020 study

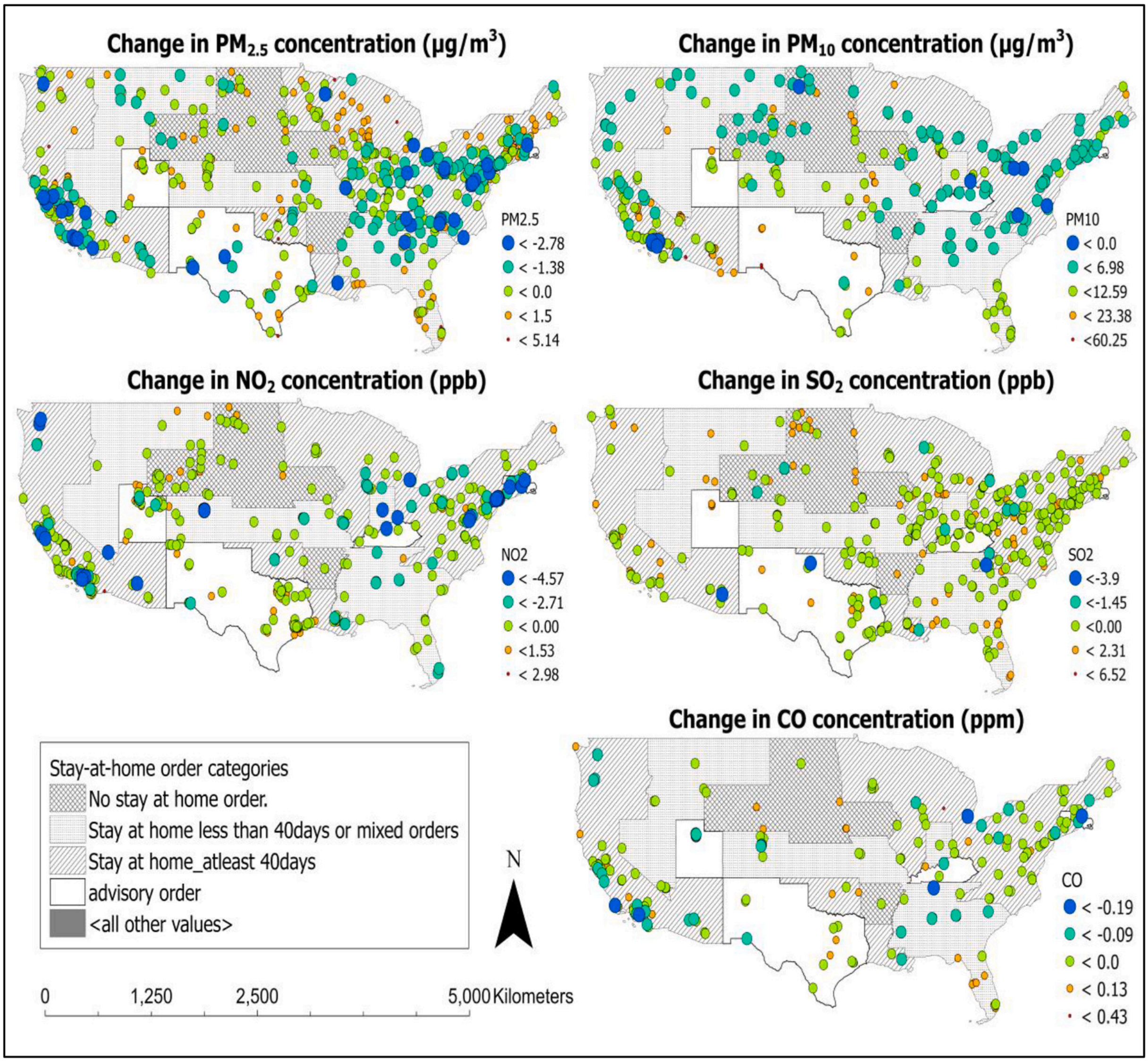

Fig. 3. $PM_{2.5}$, PM_{10}, SO_2, NO_2 and CO concentration change in 2020 shown by the location points of air quality monitoring stations.

period. Since CO reduction was not statistically associated with the stay-at-home categories in the previous Chi-square test, we did not include a percent decrease in CO levels in the figure. The major finding of this plot was that SO40 states were able to decrease in the $PM_{2.5}$, SO_2 and NO_2 level during the lockdown period. All stay-at-home order categories except NSO states were observed with a decrease from 10% to 12.65% in $PM_{2.5}$. The percent change in SO_2 increased in the order of SO40M, NSO and A.O. states. The highest percent changes in NO_2 levels are seen in the order of SO40, SO40M, A.O. and NSO states. However, almost all states experienced an overall increase in PM_{10} particles in 2020 compared with the previous five years which indicates rising PM_{10} sources during the study period. The scope of this study did not include identifying the sources of PM_{10} particles. The highest increase in PM_{10} concentrations occurred in the following order: A.O., NSO, SO40M and SO40 states. Despite of showing an increase in concentrations for almost all states, the states following longer stay-at-home order observed lowest increase in PM_{10} particles. Overall, the figure showed significant improvements in the air quality for the states which followed strict mitigation strategies.

In the usual scenario, the urbanized areas always contain high levels of environmental pollution compared to the surrounding rural areas. However, most cities and urban regions have been following strict mitigation strategies during the lockdown period of March to June, varying from one state to another. This decrease in regular movements and interactions within the city areas might have benefited and improved the environment, specifically the quality of air. Hence, we studied the level of particulate matter improvement in the CBSA regions where the majority of social and economic activities take place, and the population density is higher than the adjacent rural parts. However, upon collecting the CBSA AQI values for all pollutants, we observed that very few numbers of CBSAs reported AQI data for PM_{10}, SO_2, NO_2, and CO during the three months of our interest. These limited AQI values of PM_{10}, SO_2, NO_2, and CO for our study period do not represent an ideal observation in AQI change for four stay-at-home order categories. Hence, we decided to analyze the changes in $PM_{2.5}$ AQI values only.

Fig. 5 illustrates the percent change in $PM_{2.5}$ AQI values within the CBSA boundaries and their aggregated changes over the stay-at-home order categories. The negative values in the Fig. 5(a) legend means reduction in AQI values as percent changes of the historical AQI values from previous five years. And the (%) change values have been categorized into 3 classes for both positive (>0%) and negative (<0%) change in AQI values to observe the maximum and minimum ranges of increase (+) or decrease (−) in AQI. Fig. 5(a) shows that the CBSAs mostly experiencing <0% change in AQI, falls within the SO40 and SO40M boundaries which indicates higher percent reductions for these CBSAs. It is easier to compare the major implications of different stay-at-some orders if the CBSA AQI values are aggregated into SO40, SO40M, A.O. and NSO regions. The aggregated value of AQI changes observed in CBSA boundaries are shown in Fig. 5(b). The visual comparison indicates that the CBSA areas experience an overall improvement in $PM_{2.5}$ AQI values. The highest AQI reductions in percentage are seen in the SO40 states followed by the SO40M, A.O., and NSO states. This proves that the states restricting social activities for more than 40 days were able to experience the best overall improvement in $PM_{2.5}$.

We also investigated to find out if the mandatory state stay-at-home orders were able to reduce the COVID-19 infection and death rate by limiting the population interactions and their movements. We intended to study the effects of these restrictions over time and population size in terms of two indices: diffusivity (D) and lethality (L). Diffusivity was estimated with daily infection cases as a percentage of individual state population Eq. (1), while lethality was calculated with daily COVID-19 death cases as a percentage of state population Eq. (2). We also estimated the daily death rate as a percentage of COVID-19 infected cases using Eq. (3).

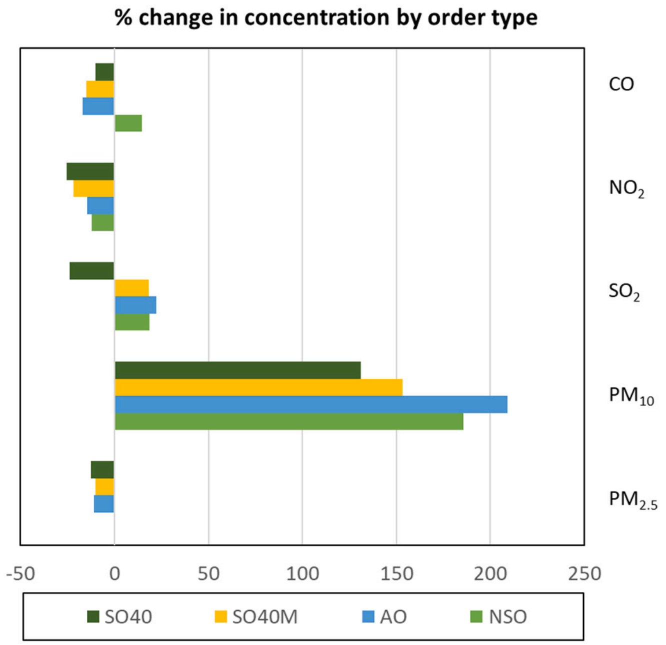

Fig. 4. Percentage change in $PM_{2.5}$, PM_{10}, SO_2 and NO_2 concentrations by 4 stay-at-home order categories.

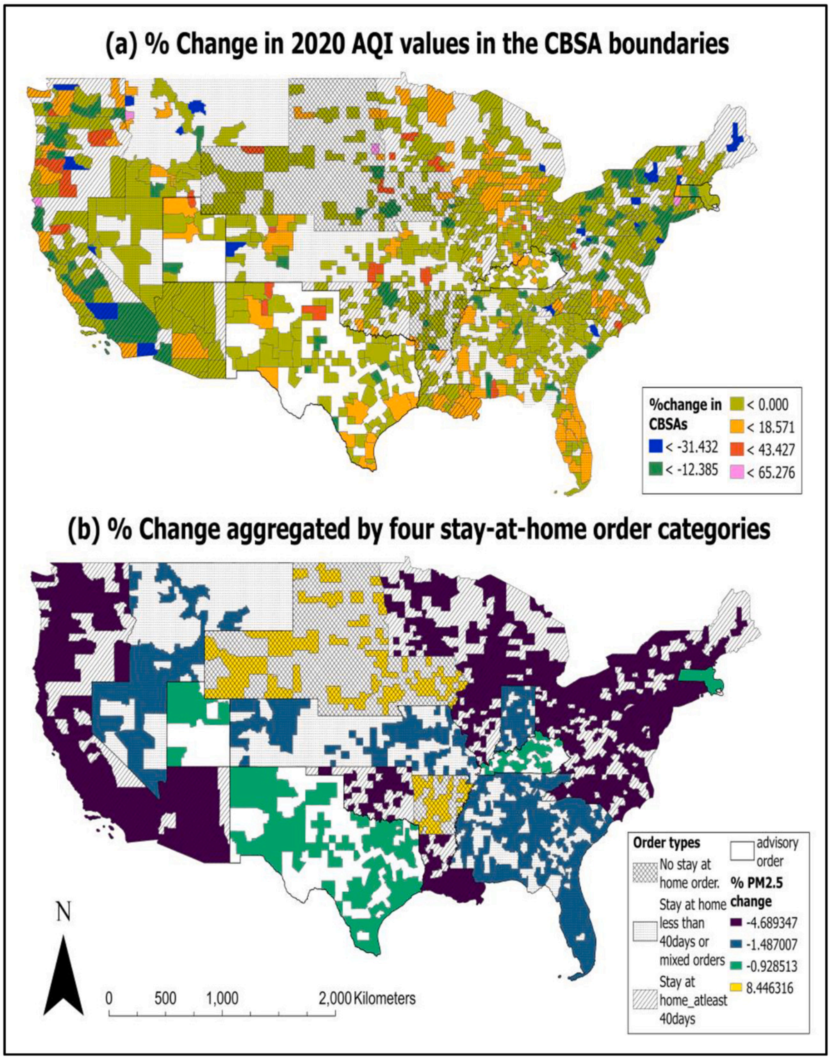

Fig. 5. Percentage change in 2020 $PM_{2.5}$ AQI values in the CBSA areas and the aggregated AQI change (%) by the stay-at-home order categories (Note: Shaded areas in both figures represent the CBSA areas).

$$Diffusivity\ (D) = \frac{Daily\ new\ COVID-19\ cases\ in\ a\ state}{Population\ of\ the\ state} * 100\% \tag{1}$$

$$Lethality\ (L) = \frac{Daily\ new\ COVID-19\ deaths\ in\ a\ state}{Population\ of\ the\ state} * 100\% \tag{2}$$

$$Death\ rate\ over\ infected\ cases = \frac{Daily\ new\ COVID-19\ deaths\ in\ a\ state}{Daily\ new\ COVID-19\ cases\ in\ a\ state} * 100\% \tag{3}$$

Then, the daily diffusivity and lethality rates were aggregated as monthly average rates for each stay-at-home category. The monthly average values were calculated for the whole year of 2020 in order to observe the possible trends and the peak death rate. Fig. 6 creates two charts for diffusivity and lethality which plot monthly infection and death rates for each stay-at-home order type from January 2020 to January 2021.

Fig. 6(a) shows that the rate of infection over population have increased for all states throughout the entire year of 2020. However, after analyzing the diffusivity trendlines for each stay-at-home order category, the lowest slope (0.127 case/month) was observed for the SO40 states followed by the SO40M (0.168 case/month), A.O. (0.17 case/month) and NSO states (0.201 case/month). Similarly, Fig. 6(b) shows that the rate of lethality over state population seemed to increase from January to December of 2020 throughout the states. SO40 states had the lowest lethality slope (0.127 death/month) which is followed by the A.O. (0.0017 death/month), SO40M (0.0021 death/month), and NSO states (0.0021 death/month). The states following no stay-at-home order experienced highest

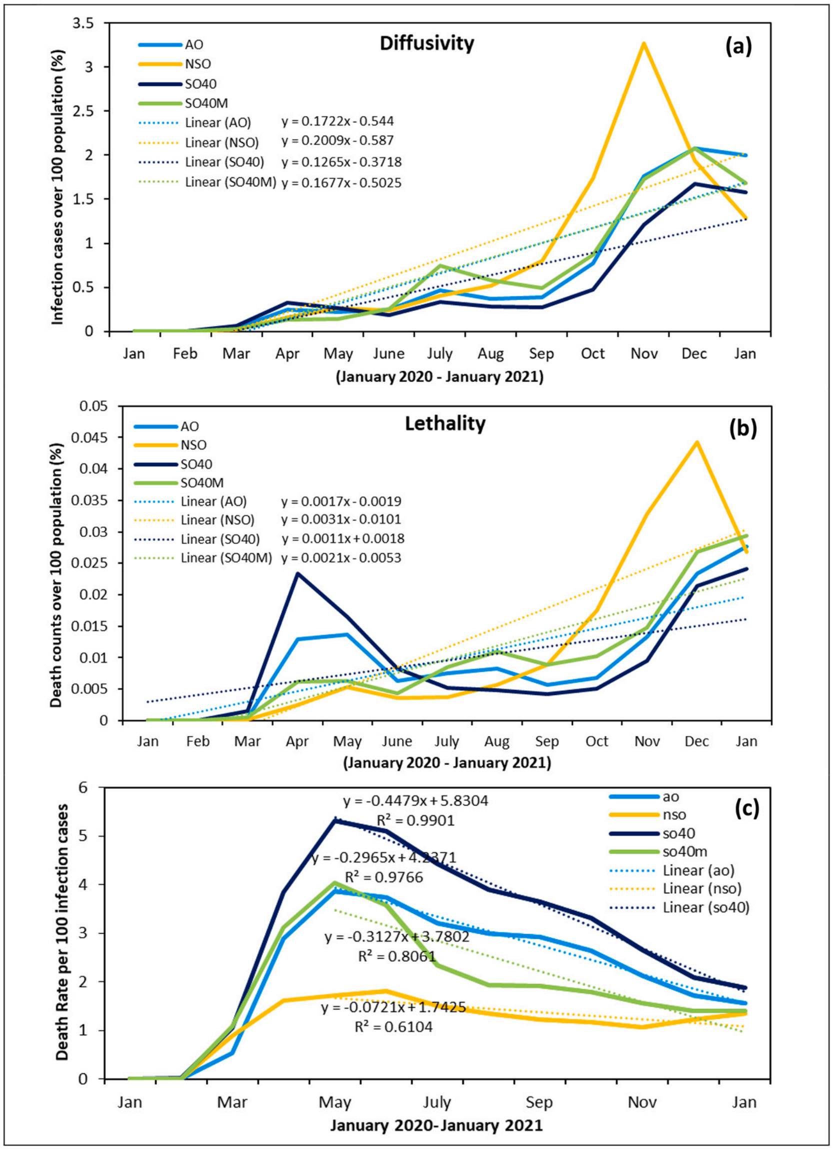

Fig. 6. % Implications of the stay-at-home order categories on the diffusivity (a), lethality (b) of the pandemic and death rates over infection cases (c).

increase in diffusivity and lethality.

Moreover, we observed the death rates over infection cases peaking in May for all order categories in Fig. 6(c). Though the majority of the states began implementing public health measures in March of 2020, all four jurisdictions of stay-at-home orders experienced a peak at the same time in May with varying death rates depending on several other factors, such as population density and travel patterns. It would be interesting to see if different mitigation measures have played any role in reducing the COVID-19 mortality rate throughout the whole year. Therefore, we noticed the mortality trends for each measure starting from the peak time to January 2021 when the death rates significantly reduced for all states. The figure shows that the states issuing stay-at-home orders for more than 40 days were able to reduce 0.44 death/month with a best fitting line ($R^2 = 0.99$). SO40M and A.O. states had a reduction of 0.313 ($R^2 = 0.98$) and 0.29 death/month ($R^2 = 0.81$), respectively. However, the death rate had negligible decreases (0.07 death/month) with a moderate fitting line ($R^2 = 0.61$) for the states without any stay-at-home order and showed a slightly increasing rate since November 2020. The NSO states had shown lower death rates since the beginning of the COVID-19 transmission.

4. Conclusion

From March, stay-at-home orders were issued by different states as a community mitigation strategy to control and reduce the

COVID-19 spread throughout the country. In our study, we explored the implications of these public health measures on overall air quality and the COVID-19 mortality rate. Our analysis introduced several important findings regarding these mitigation measures in the contiguous U.S.

Our initial finding was that the states classified in terms of the type and duration of stay-at-home orders vary in the levels of air pollutants and are comparable for in-depth analysis. Comparing the level of $PM_{2.5}$, PM_{10}, SO_2, NO_2, and CO reductions between these measures show significant declines of the concentrations values in the states that followed longer periods of stay-at-home orders. However, states without any measure had insignificant reductions in the $PM_{2.5}$, SO_2, NO_2 and CO levels. Also, we found that the type of these four measures and the decrease in air pollution, except for CO, from March to June 2020, were statistically associated. States with advisory orders and without any orders found to be mostly associated with increased $PM_{2.5}$, NO_2, and SO_2 pollutions. The scatterplots of the pollutants' concentrations between recent and historic years for all monitoring stations showed that the states following stay-at-home orders for more than 40 days or states following order less than 40 days or mixed orders have the highest decrease in $PM_{2.5}$ and NO_2. The states following strict stay-at-home orders were able to reduce the concentrations of $PM_{2.5}$, PM_{10}, SO_2, and NO_2. The $PM_{2.5}$ concentration had a maximum reduction of 7.3 $\mu g/m^3$ but also a maximum increase of 5.14 $\mu g/m^3$ within the contiguous U.S. Most stations showing a $PM_{2.5}$ concentration reduction are located in the states following stay-at-home orders for at least 40 days. SO_2 and CO were noticed to be with the highest decreases of 4.8 ppb in North Carolina and 0.296 ppm in California, respectively. States following mitigation measures for longer periods were able to decrease the $PM_{2.5}$, SO_2, and NO_2 concentrations during the lockdown period. Almost all states experienced an overall increase in the concentration of PM_{10} particles in 2020 compared to the past five years. Our analysis of $PM_{2.5}$ AQI levels within the urbanized areas shows air quality improvements in most urban areas with the highest improvements in the states following longer stay-at-home orders. Moreover, the longer mitigation policies (in the SO40 states) significantly helped to reduce the COVID-19 mortality rates over infection (0.44 death/month) from the peak season of transmission. These states also experienced slowest increase in the diffusivity (0.127 infection case/month) and lethality (0.0011 death/month) of the pandemic over their population size.

There are, however, certain limitations in our study. Since each state possesses the authority to issue its own policies, the states might vary in detailed policies in controlling public movements. The policy differences within the states can also play an important role in affecting air quality and mortality rate. But due to lack of data, we used four broad classifications of stay-at-home orders. Moreover, this study included ground-based air quality data to be aggregated within the stay-at-home order categories. To preserve the observation values, we did not use any interpolated outputs representing the missing air quality data. The findings from this study provides important insights about the implications of various public health policies in relation to the overall condition of air quality and COVID-19 mortality.

Credit author statement

All persons who meet authorship criteria are listed as authors, and all authors certify that they have participated sufficiently in the work to take public responsibility for the content, including participation in the concept, design, analysis, writing, or revision of the manuscript. Furthermore, each author certifies that this material or similar material has not been and will not be submitted to or published in any other publication before its appearance in this journal.

Authorship contributions

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Writing - original draft, Visualization: S. Sabrin

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Declaration of Competing Interest

None.

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