A Spatio-temporal Study of Changes in Air Quality from Pre-COVID Era to Post-COVID Era in Chicago, USA

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ABSTRACT

The COVID-19 pandemic has drastically changed human life and the world's environment. Most of the major cities of the USA went under full or partial lockdown in the first half of 2020. However, it started gradually reopening, and in 2021, most of the public activity restrictions were lifted. Many studies reported a significant improvement in air quality during the COVID-19 pandemic in the USA, corresponding with the reduced human activity. We hypothesized that this improved air quality was followed by the decline to air quality again due to the normalization of human activity in 2021. This study is a novel approach of studying air quality using spatio-temporal analysis at the finer spatial level within a city in the USA. It assessed the change in six air quality parameters from the pre-COVID era to the post-COVID era in Chicago city in Illinois, USA. The study found that reduced human activities during COVID-19, improved air quality by reducing the concentration of some air pollutants, especially PM2.5, NO2, and CO. However, this improvement was transitory, and it reverted in the post-COVID era. Therefore, policies should be formulated and practiced to improve air quality in the long term.

Keywords: COVID-19, Air pollution, Urban air quality, NO2, Particulate matter

1 INTRODUCTION

The unprecedented coronavirus disease 2019 (COVID-19) pandemic has drastically changed the world's human life and environment. The pandemic has affected more than 351 million people and killed more than 5.6 million lives worldwide as of January 2022 (CRC, 2022). It has also caused enormous economic, public health, and social damage. The World Health Organization (WHO) announced COVID-19 as a pandemic on March 11, 2020 (Archer et al., 2020). The pandemic has created many challenges for the United States (US) government to balance the economy and public safety. As a result, the USA declared a national emergency on March 13, 2020. Most of the major cities of the USA went under full or partial lockdown. Thus, the human movement was limited at that time. It also caused a reduction in road traffic in that period (Hudda et al., 2020; Parker et al., 2020; Tokey, 2021).

While the world population were under lockdown and experiencing health risk, one of the rare benefits that the world has experienced is the improvement in air quality globally due to societal efforts and policies to mitigate COVID-19 by different measures, including the prohibition on mass gathering, social distancing, shutting-down of non-essential industries and the restriction of public transportation (Liu et al., 2021). As a result, the COVID-19 restrictions have reduced the emission of the primary air pollutants worldwide in general and particularly in the United States, due to the decrease in industrial activities and transportation (Taquechel et al., 2020). For example, the US National Oceanic and Atmospheric Administration stated an almost 30% decrease in nitrogen dioxides (NO2) emissions in the urban northeast during April 2020 (Zhang et al., 2021).
In addition, there was a massive reduction in the volatile organic compound concentrations (Zhang et al., 2021).

Air pollution has a detrimental effect on human health, the climate, and sustainable development (Guo et al., 2021). Research studies have proven that exposure to the fine particulate matter (PM), especially PM$_{2.5}$, may cause significant harmful health effects, including cardiovascular, respiratory, diabetes, kidney disease mortality, and morbidity (Bowe et al., 2021; Chen et al., 2021) that lead to millions of premature deaths across the world every year (Karaer et al., 2020). The WHO estimates that 4.2 million people die each year due to exposure to air pollution (Archer et al., 2020; WHO, 2020). Additionally, ecological studies indicate that living in areas with high levels of ambient fine particulate matter increases the risk of adverse COVID-19 outcomes (Bowe et al., 2021). Though COVID-19 restrictions have improved air quality globally by reducing the emission of air pollutants, this effect might be transitory. Though coronavirus continues to affect human beings badly, the US has achieved a significant improvement in controlling COVID-19 by providing vaccines and other mitigatory measures (Diesel et al., 2021). Thus, almost everything went back to normal life. This return might cause air quality to decline and match the pre-COVID-19 era. As a result, the evaluation of air quality in the post-COVID era is necessary for policymakers.

Many studies attempted to assess the change in the air quality of the US during the pandemic. Though some studies reported a decline in air pollutants and significant improvement in air quality (Berman and Ebisu, 2020; Chen et al., 2020; Liu et al., 2021; Parker et al., 2020), some studies also reported no significant improvement in air quality (Adhikari and Yin, 2020; Archer et al., 2020; Pata, 2020; Razzaq et al., 2020), even increase of air pollutant in some cases (Bekbulat et al., 2021; Perera et al., 2021; Shakoor et al., 2020). In addition, the range of change in air quality in different studies is very wide. While analysis at the finer spatial level can give more insight into this issue, few studies conducted spatio-temporal analysis over the whole US or at the state level. None of the studies explored microclimate within a finer spatial extent, i.e., within city level (community area within a city). Moreover, those few spatio-temporal studies used larger spatial extents with low-resolution remote sensing images (Bar et al., 2021; Kerr et al., 2021; Naeger and Murphy, 2020). Again, to the best of our knowledge, no studies in the US attempted to examine the air quality using all six parameters of air quality by the U.S. Environmental Protection Agency (U.S. EPA) (Tables 1 and 2).

This study conducts a spatio-temporal analysis of the change of air quality, i.e., six parameters of air quality of Chicago city in 2020, and compares the spatio-temporal pattern in previous (2019)

### Table 1. Definitive findings of studies conducted in the USA.

| Sl. | Study Area | Change in Air Quality Parameter (%) | Source |
|-----|------------|-------------------------------------|--------|
| 1   | USA        | PM$_{2.5}$ | PM$_{10}$ | CO | NO$_{2}$ | O$_{3}$ | SO$_{2}$ | (Bar et al., 2021) |
| 2   | USA        | +3         | –         | – | –18 to –40 | – | – | (Bekbulat et al., 2021) |
| 3   | USA        | +3.51 to –11.26 | – | – | –5.52 to –26.89 | – | – | (Berman and Ebisu, 2020) |
| 4   | USA        | –          | –         | – | –11 | – | – | (Gillingham et al., 2020) |
| 5   | Florida    | –          | –         | – | –59.68 | – | – | (Karaer et al., 2020) |
| 6   | California | –31        | –         | –49 | –38 | – | – | (Liu et al., 2021) |
| 7   | California | –          | –         | – | –15 to –29 | – | – | (Liu et al., 2021) |
| 8   | Los Angeles | decrease | –         | – | –35 | – | – | (Naeger and Murphy, 2020) |
| 9   | San Francisco | decrease | –         | – | –25 | – | – | (Naeger and Murphy, 2020) |
| 10  | Southern California | –10 to –45 | – | – | –13 to –40 | +15 (down) | –22 (west) | (Parker et al., 2020) |
| 11  | USA        | +23        | –         | – | – | – | – | (Perera et al., 2021) |
| 12  | USA        | –1.1       | –27.81    | –19.28 | –36.7 | – | +3.81 | (Shakoor et al., 2020) |
| 13  | USA        | –33        | –17       | –29 | – | – | | (Xiang et al., 2020) |
| 14  | USA        | –36        | –         | – | –51 | – | – | (Zangari et al., 2020) |
and next (2021) years. The aim was to understand the change in air quality during and after the COVID-19 era. We hypothesized that the improvement of air quality during the COVID-19 pandemic corresponding with reduced human activity was followed by the decline in air quality again due to the normalization of human activity in 2021. In brief, the novelties of this study are as follows:

- Spatio-temporal study in finer spatial level, i.e., within city level (community area level) in urban areas.
- Assessing the air quality change during (2020) and after the COVID-19 era (2021).
- Considering all six air quality parameters.

The remainder of this paper is organized as follows: a review of the previous related studies is provided in Section 2; the study area, datasets, and statistical methods are introduced in Section 3; the analysis and results are discussed in Section 4, and conclusions are given in Section 5.

## 2 REVIEW OF PREVIOUS RELATED STUDIES

There were several studies conducted around the globe in 2020 to evaluate and measure the effectiveness of the COVID-19 lockdown in different countries, cities, and towns on urban air quality. Some of these findings primarily described changes in the concentrations of particulate matters such as PM$_{2.5}$, and PM$_{10}$ (PM with diameters below 10 $\mu$m), whereas other studies focused on gaseous components like NO$_2$, CO, SO$_2$, and ozone (O$_3$) in several countries around the globe (Adam et al., 2021). Previous studies have shown a decrease in the concentrations of CO, SO$_2$, and the oxides of nitrogen (NO$_x$) worldwide (Adam et al., 2021).

Specifically, a huge decrease in NO$_2$ (approximately 70%) was found in India and Spain (Sicard et al., 2020). Also, such huge decreases were described for SO$_2$ in Singapore (approximately 52%) and India (approximately 62%) as well as for CO in Brazil (> 30% and up to 100%) and India (approximately 70%) (Gautam, 2020; Resmi et al., 2020). The concentrations of PM$_{10}$, PM$_{2.5}$, NO$_2$, CO, and SO$_2$ reduced by 19%, 23%, 29%, 54%, 6%, and 52%, respectively in Singapore (Li and Tartarini, 2020). On the other hand, ozone increased by 18% during the lockdown in 2020 (April–
May) compared to the concentrations detected in the similar exact months from 2016 to 2019 (Li and Tartarini, 2020). The decline in the concentration of the major air pollutants has been recognized by the lowered emissions of air pollution from non-essential industries and on-road vehicles (Hudda et al., 2020; Rossi et al., 2020).

Other research studies discovered a strong association between the observed reductions in human mobility and reductions in NO$_2$ concentrations (Archer et al., 2020). The NO$_2$ levels were decreased by more than 4 ppb on a monthly average, where the mobility was decreased to almost 0, and around 1 ppb decline where mobility was decreased to 20% of normal or less (Archer et al., 2020). In addition, no noticeable pattern was identified between mobility and PM$_{2.5}$ concentrations. This difference suggests that decreases in personal-vehicle traffic alone could not be efficient at lowering PM$_{2.5}$ pollution (Archer et al., 2020).

Research studies have discovered that the mean of NO$_2$ concentrations significantly decreased in 2020 due to the lockdown by 18–40% over the main urban areas located in Europe, such as Paris, Madrid, and Milan, and the USA, such as Boston, Springfield, and New York (Bar et al., 2021). However, other research findings showed that the enormous changes from the COVID-19 response have not decreased PM$_{2.5}$ levels across the United States beyond their normal range. In addition, the CO, NO$_2$, O$_3$, and PM$_{10}$ concentrations were decreased, but the reduction was transient and modest (Bekbulat et al., 2021).

More than 25 studies were conducted in the United States about the effect of the COVID-19 lockdown on the concentration of NO$_2$, CO, SO$_2$, PM$_{2.5}$, PM$_{10}$, and O$_3$. The major US states such as Texas, California, Illinois, and New York clearly showed a reduction in the concentration of NO$_2$ and CO during the COVID-19 lockdown (Elshorbany et al., 2021). These reductions were, in many cases, affected by meteorological conditions or compensated by local emissions (Elshorbany et al., 2021). Some research analyses in the US showed a statistically significant reduction in the concentration of particulate matter across most of the regions during the COVID-19 lockdown (Ghosal and Saha, 2021). For example, in California, the ground-based observations showed a 31%, 38%, and 49% drop in the concentration of PM$_{2.5}$, NO$_2$, and carbon monoxide (CO) during the lockdown period between March 19 and May 7 compared to the period of January 26 until March 19 in 2020 (Liu et al., 2021). These are 19%, 16%, and 25% greater than the means of the previous five years in the same time periods, respectively (Liu et al., 2021).

A study conducted in New York indicated an almost 23% improvement in PM$_{2.5}$ levels during the COVID-19 shutdown compared to the average level for the same months period in 2015–2018 (Perera et al., 2021). In addition, some research studies indicated that the overall concentrations of NO$_2$, PM$_{2.5}$, and CO were decreased by 37%, 1%, and 19%, respectively, while SO$_2$ and PM$_{10}$ were increased by 4% and 28%, respectively, in five states of the USA during the lockdown (Shakoor et al., 2020). On the other hand, the overall concentration was reduced by 38% for PM$_{10}$, 18% for PM$_{2.5}$, 18% for SO$_2$, and 39% for CO in all the selected provinces of China (Shakoor et al., 2020).

In Pittsburgh, Pennsylvania, studies showed no significant change in the industry-related intraday adaptability of PM$_{2.5}$ and CO in the industrial areas after the COVID-19 related closures (Tanzer-Gruener et al., 2020). In addition, in New York City, some studies have indicated a significant decrease in NO$_2$ (51%) and PM$_{2.5}$ (36%) concentrations were observed after an abbreviated period right after the shutdown took place, but there was no significant difference compared with the same span of time in 2015–2019 (Zangari et al., 2020).

From the results of the previous studies, we noticed that some studies reported an increase in air pollutants and a major improvement in air quality. On the other hand, some studies reported no significant improvement in air quality or even an increase in the air pollutants in some cities and states. It is important to mention that there are no studies in the US that measure the effectiveness of the COVID-19 lockdown on air quality at a finer spatial level within a city using all six air pollutants set by EPA: CO, SO$_2$, NO$_2$, O$_3$, PM$_{2.5}$, and PM$_{10}$.

### 3 METHODOLOGY AND MATERIALS

#### 3.1 Study Area

Chicago city of Illinois, USA, was selected as the study area to evaluate the air quality at a finer
spatial level. With its 2.67 million people, Chicago is the third-most populous city in the US and the most populous city in Illinois state (World Population Review, 2022). In addition, the city is a major national hub of transport at the crossroads of the USA’s rail, road, and air traffic, with one of the largest international airports. In recent years, transport emissions have been Chicago’s largest emission source (IQAir, 2022). With the exacerbating condition of COVID-19, the governor of Illinois declared the stay-at-home order on March 21, 2020. However, after gaining initial control of the spread of coronavirus, it started to reopen on May 29, 2020.

### 3.2 Data

The EPA open-source ground sensor-based data were downloaded for three years (from 2019 to 2021) from the AirNow website (https://www.epa.gov/outdoor-air-quality-data/download-daily-data) on the first week of January 2022. Data were collected for six air quality parameters set by EPA: daily maximum 1-hour NO2 and SO2, daily maximum 8-hours for CO and O3, and daily 24-hour average concentrations for PM2.5 and PM10 for all available monitoring stations. Then, the daily average was calculated based on data of all available stations on that date. Georeferencing has been done using stations’ latitude and longitude to convert the dataframe into geospatial point dataframe. Finally, spatial filtering was used to keep the Chicago city area data only.

Three years were treated as three eras, i.e., 2019, 2020, and 2021 for pre, peri, and post COVID-19 eras, respectively. As we mentioned earlier, the state of Illinois declared stay-at-home order on March 21, 2020, and reopened on May 29, 2020; each era (i.e., each year) was classified in three timespans: from January 1 to March 20 as “before”, from March 21 to May 29 as “during” and May 30 to June 30 as “after” the stay-at-home period. The “before”, “during”, and “after stay-at-home orders” were used as generalized terms, though the stay-at-home order was only observed in 2020. These terms will refer to the respective period of each year as stated above. In the post-COVID era air quality assessment, the monthly average for the whole year in each era also has been calculated. In addition, population demographic data was downloaded from the website of the US census (https://www.census.gov/programs-surveys/decennial-census/about/rdo/summary-files.html). This data was pre-processed using the R script provided by the census
and was merged with the census TIGER/Line shapefiles to georeferenced it. Finally, it was exported to geodatabase using SQL.

### 3.3 Methods of Statistical Analysis

To compare the air quality in three periods of three years, along with time series and trend analysis, locally estimated scatterplot smoothing (LOESS) was employed to smooth out daily fluctuations in air quality monitoring. However, enough ground observation points for spatial variation analysis were unavailable for all six air pollutants. Therefore, we only analyzed spatial variation in PM$_{2.5}$, NO$_x$, and O$_3$.

As the air quality observation stations are spatially discrete points, to formulate continuous spatial surfaces for each air quality parameter, we used spatial interpolation, more specifically inverse distance weighting (IDW) methods. Spatial interpolation is the process of using points with known values to estimate values at other points. IDW is one of the most popular exact spatial interpolation methods that estimate an unknown value as the weighted average of its neighboring points, in which the weight is the inverse of the distance raised to a power (Chang, 2004). The IDW is expressed as below,

$$Z_u = \frac{\sum_{i=1}^{s} Z_i d_{iu}^{-k}}{\sum_{i=1}^{s} d_{iu}^{-k}}$$

where $Z_u$ is the unknown value to be estimated at $u$, $Z_i$ is the attribute value at control point $i$, $d_{iu}$ is the distance between points $i$ and $u$, $s$ is the number of control points used in estimation, and $k$ is the power (Wang, 2015).

### 4 RESULTS AND DISCUSSION

#### 4.1 Temporal Change in Air Pollutants

##### 4.1.1 Change in particulate matter concentration

Analysis of PM$_{2.5}$ revealed that the daily mean concentration of PM$_{2.5}$ in three periods of 2020 was less than respective periods of both 2019 and 2021, except after the stay-at-home period in 2021 (Fig. 2). In addition, PM$_{2.5}$ concentration during the stay-at-home period was less than before and after (5% less than before) in that year (2020). This result indicates that due to the COVID-19 pandemic, PM$_{2.5}$ concentration was lower than the previous year. Again, after the stay-at-home period, PM$_{2.5}$ concentration increased. This change might result from increased human activities after the reopening on May 29. In 2021, PM$_{2.5}$ concentration increased again, and it was greater than the concentration in 2020. Thus, the beneficial effect of COVID-19 lockdown in PM$_{2.5}$ concentration might be transitory. One common thing in all three years is that PM$_{2.5}$ concentration was lower in stay-at-home periods in all three years. Therefore, there might be a seasonality effect, which can be explained by trend analysis. Also, a decrease in PM$_{2.5}$ concentration in the stay-at-home period cannot solely be contributed by reduced human activity if there are similar seasonal trends in other years.

Now, from the analysis of the trend of daily mean PM$_{2.5}$ concentration, it is seen that there was always a peak and fall in all three eras (years) (Fig. 3), and the slope was not consistent all over the years. Still, the pattern in 2019 and 2021 is nearly similar. In 2020, it started to decline in mid-February, which was the opposite of 2019 and 2021. Though the stay-at-home period started on March 21, 2020, there were other mitigatory measures before stay-at-home. For instance, the governor of Illinois declared Illinois a disaster area on March 9, prohibiting mass gatherings on March 13, and ordered the closure of restaurants and March 16. It is worth mentioning that the initial stay-at-home order was up to April 30, 2020. However, it extended to May 29, 2020, reducing some restrictions.

Analysis of PM$_{10}$ concentration showed a different result than PM$_{2.5}$. The mean concentration of PM$_{10}$ in 2020 was slightly higher both before and during the stay-at-home period in 2020 with
respect to the equivalent periods of 2019 (Fig. 2). However, it was much higher after the stay-at-home period than during the stay-at-home period in 2020 (50%). In 2021, the mean concentration was greater than in the previous two years. These findings are also evident in trend analysis of daily mean PM10 concentrations (Fig. 3). After the stay-at-home period, PM10 concentration got a sudden spike. This spike could be a direct result of increasing activities after the reopening. Additionally, it is also apparent that, though the trend of PM10 concentration is much higher in 2021 than in the previous two years, it follows a nearly similar rising and fall as of 2019. However, the trend in 2020 was different. In addition, it is seen that there is an increasing trend from 2019 to 2021. Therefore, it can be said that, though the PM10 concentration was a little bit higher before and during stay-at-home in 2020 than the respective period in 2019, it could be much higher without stay-at-home order.

The difference in the effect of COVID-19 on PM2.5 and PM10 concentrations can be explained by the source of particulate matter. The main sources of particulate matter are the combustion of fossil fuels (both vehicle and residential fuel combustion), industrial processes, fugitive dust (wind and mechanical erosion of local soil), and photochemically produced particles (Illinois EPA, 2020). Combustion and photochemical products tend to be a smaller size (PM2.5 - PM with diameters below 2.5 μm), while fugitive dust and industrial products are typically larger in size.
4.1.2 Change in concentration of gaseous compounds in air

Similar to the particulate matters, all gaseous components of air did not show the same response in COVID-19 stay-at-home periods. In 2020, the mean concentration of NO$_2$ before the stay-at-home period was 28.17 ppb which was reduced during stay-at-home periods to 26.79 ppb (decrease by 5%) and increased to 27.93 ppb (increase by 4%) after the stay-at-home period (Fig. 2). If we compare the NO$_2$ concentration in these periods in three years, we see that before and during the stay-at-home period, the concentration of NO$_2$ was lower than in the same periods in both 2019 and 2021 but higher after the stay-at-home period. This result indicates that due to the stay-at-home order and other mitigatory measures before the stay-at-home order, the concentration of NO$_2$ was reduced. However, with the end of the stay-at-home period, it increases again. In addition, it increases in post COVID era (in 2021) and is nearly similar to 2019.
Now, from the trend of NO\textsubscript{2} concentration, it is seen that at the beginning of January, all three years experienced an uprising of NO\textsubscript{2} concentrations (Fig. 3). In mid-February of 2020, it started to decrease and was relatively stable up to the end of April. Then, it spiked after the stay-at-home period. As discussed earlier, the early decrease in NO\textsubscript{2} concentrations can be attributed to the early COVID-19 response before the stay-at-home order.

Compared to NO\textsubscript{2}, no immediate drops were observed during the stay-at-home in case CO, SO\textsubscript{2}, and O\textsubscript{3} (Fig. 2) in 2020. The mean concentration of these three air pollutants increased by 3\%, 34\%, and 32\%, respectively. These even further increase after the stay-at-home period. This analysis might not be a fair comparison due to seasonality and trend. However, CO and O\textsubscript{3} concentrations were lower before and during the stay-at-home periods in 2020 than in equivalent periods of the previous year. On the contrary, this scenario is the opposite in the case of SO\textsubscript{2}.

Though the trend of the daily mean concentration of CO, SO\textsubscript{2}, and O\textsubscript{3} was not always consistent, there is still a similar upward trend of these three air pollutants in all three years (Fig. 3). Thus, the increase in CO, SO\textsubscript{2}, and O\textsubscript{3} after stay-at-home in 2020 cannot be entirely attributed to reopening after stay-at-home. In general, CO concentrations decreased in the post COVID era (2021). On the contrary, both SO\textsubscript{2} and O\textsubscript{3} have increased in post COVID era.

The source of these four gaseous components can explain the difference in the impact of COVID-19 on the concentration of these pollutants. NO\textsubscript{2} comes from fossil-burning sources such as vehicles, power plants, and industrial emissions (Liu et al., 2021). As road traffic was reduced and industries were shut down, NO\textsubscript{2} declined. The major source of CO is motor vehicles (Illinois EPA, 2020). With the reduction of traffic volume, CO concentration should decline. However, CO has another type of source, that is indoor fuel-burning appliances (Liu et al., 2021). As more people were at home, there was a chance of more use of these appliances, which can cause an increase in CO concentration. O\textsubscript{3} is a photochemical secondary oxidation product created when nitrogen oxides (NO\textsubscript{x}) and volatile organic compounds (VOCs) react in warmer temperatures and sunlight. Since it occurs at a warmer temperature, it is much more prevalent in the summer than in winter (IQAir, 2022). Thus, all three years showed an uprising trend up to June. O\textsubscript{3} can be more limited by VOCs than NO\textsubscript{x} in the NO\textsubscript{x}-rich urban air, and thus reducing NO\textsubscript{x} emissions would increase O\textsubscript{3} unless VOCs are reduced at a higher rate at the same time (Chen et al., 2020; Kleinman et al., 2005).

### 4.2 Spatio-temporal Change in Air Pollutants

Analysis of the spatio-temporal change revealed a similar result to what we found in the previous section, with some exceptions. For instance, while the average concentration of PM\textsubscript{2.5} during the stay-at-home period in both 2019 and 2021 was higher than the respective period in 2020, spatio-temporal analysis shows a slightly opposite relation. The range of spatial variation was larger in 2020 compared to the respective periods of previous and next year. This variation implies that, though, on average, PM\textsubscript{2.5} concentration was lower in the stay-at-home period in 2020, there were few point locations where PM\textsubscript{2.5} was increased. In addition, NO\textsubscript{2} concentration in 2021 after the stay-at-home period is greater than the respective period of 2020, though it was lower in temporal analysis. In general, all three air pollutants show a reduction in concentration during the stay-at-home period in 2020 compared to the respective period of 2019.

There was notable spatial variation in PM\textsubscript{2.5} concentrations in all three periods in all three years (Fig. 4). The southwest industrial part of the city was always a high PM\textsubscript{2.5} concentration area in all periods in all three years except the stay-at-home period in 2020. This variation indicates that the closure of industries contributed to reducing PM\textsubscript{2.5} concentration. In addition, the Chicago airport area was always a high concentration area in all three years compared to the concentration in other parts of the city in any period. While the middle part of the city was a low PM\textsubscript{2.5} concentration area before the stay-at-home period, it turned into a high concentration area during the stay-at-home period in 2020.

High O\textsubscript{3} concentration was predominantly observed in the eastern part of the city (Fig. 5). We mentioned earlier that O\textsubscript{3} formation occurred at higher temperatures. Some studies found that the eastern part of Chicago city is usually exposed to higher temperatures due to the warming effect of Lake Michigan in colder weather (English et al., 2020). The O\textsubscript{3} concentration was also higher in the southwest industrial area.
Fig. 4. Spatio-temporal variations in PM$_{2.5}$ in three periods of three eras: (A-1) before, (A-2) during, and (A-3) after stay-at-home periods in the pre-COVID era (2019), (B-1) before, (B-2) during and (B-3) after stay-at-home periods in peri-COVID era (2020), (C-1) before, (C-2) during and (C-3) after stay-at-home periods in post-COVID era (2021).
Fig. 5. Spatio-temporal variations in $O_3$ in three periods of three eras: (A-1) before, (A-2) during, and (A-3) after stay-at-home periods in the pre-COVID era (2019), (B-1) before, (B-2) during and (B-3) after stay-at-home periods in peri-COVID era (2020), (C-1) before, (C-2) during and (C-3) after stay-at-home periods in post-COVID era (2021).
Fig. 6. Spatio-temporal variations in NO₂ in three periods of three eras: (A-1) before, (A-2) during, and (A-3) after stay-at-home periods in the pre-COVID era (2019), (B-1) before, (B-2) during and (B-3) after stay-at-home periods in peri-COVID era (2020), (C-1) before, (C-2) during and (C-3) after stay-at-home periods in post-COVID era (2021).
The concentration of NO$_2$ was always higher in the Chicago airport area during all periods in all three years (Fig. 6). In addition, the downtown area where population density is higher, was also a high NO$_2$ concentration zone for 2020 and 2021. In general, NO$_2$ is lower in the lower middle part of the city, where population density is comparatively lower (Fig. 1).

Due to the low number of monitoring stations, the spatial surface created by spatial interpolation might not resemble the actual pollution surface. Still, it is a reasonable estimation of spatial variation in air pollution. In addition, the spatial variation of these three air pollutants could be better explained by the land use, built environment, vegetation index, industrial presence, population demographic profile, weather, and environmental factors.

### 4.3 Monthly Change in Air Quality during and Post-COVID Era

The average concentration of PM$_{2.5}$ concentration was lower every month in 2020 compared to the respective month in 2019 (Fig. 7). It reduced from a range of 0.03% to 29.03% in different months. However, the concentration of PM$_{2.5}$ increased in 2021 almost every month except June, September, and December. While February experienced the highest reduction in 2020, it also showed the highest increase in 2021. In the case of PM$_{10}$ concentration, it increased in 2020 every month except February, March, and December (Fig. 7). Though it started to increase earlier in the year, after May, it shows a higher percentage increase than in 2019. It continued to increase in 2021. While it shows an increase in concentrations up to May, it started to decline after May.

NO$_2$ concentration was lower in the first five months of 2020 than in the respective month of 2019 (Fig. 7). From June to August, it shows an increase in NO$_2$. However, the percentage increase was lower than the percentage of reduction that happened earlier in the year. In 2021, it showed the exact opposite scenario. The months that experienced a reduction of NO$_2$ concentration in 2020, show an increase in 2021. The concentration of CO in 2020 was lower in every month compared to the respective month of 2019 except for July (Fig. 7). However, these changes were higher in the last three months of the year. It also shows a reduction in the first half of 2021 and increases with a very high percentage in the last three months.

SO$_2$ experienced an increase in the concentration in 2020 up to August except for February and May (Fig. 7). It shows the decline in the later part of the year. The month which experienced an increase in 2020 shows a decline in 2021. It is also partially true for O$_3$ concentrations. O$_3$ concentrations were lower in the first four months of 2020.

In general, all six air pollutants show a change in the opposite direction in most months in the peri-COVID (2020) and post-COVID era (2021). It indicates that the post-COVID era experienced a reverse direction change than what happened in the COVID era. Most likely, normal activities that were almost restored in 2021 caused air pollutants to return to the normal cycle of the pre-COVID era. It can be concluded that the concentration of PM$_{2.5}$, NO$_2$, and CO has been reduced in 2020 and increases again in 2021 except for CO. The concentration of SO$_2$ increased during the COVID era and in the post-COVID era.

### 5 CONCLUSIONS

This study evaluated the effect of COVID-19 on air quality by analyzing the spatio-temporal changes in the concentrations of six air pollutants from the pre-COVID era (2019) to post-COVID (2021). The study found that PM$_{2.5}$ and NO$_2$ concentration was reduced during the stay-at-home period in 2020, and it increased after the stay-at-home due to the resumption of activities. In general, these two pollutants were lower than the previous year and increased in the post-COVID era. On the other hand, the mean concentration of CO, SO$_2$, and O$_3$ increased during the stay-at-home period. These even further increase after the stay-at-home period. These three pollutants, especially O$_3$, show an increasing trend in all three years. Thus, the increase in CO, SO$_2$, and O$_3$ after stay-at-home in 2020 cannot be solely attributed to reopening after stay-at-home. In general, CO concentrations decreased in the post COVID era (2021). On the contrary, both SO$_2$ and O$_3$ have increased in post COVID era. PM$_{10}$ concentration increases slightly during the stay-at-home period and becomes higher after the stay-at-home period. In 2020, PM$_{10}$ concentration was much higher than in 2019 and continued to increase in the post-COVID era. Considering the increasing trend from 2019 to 2021, it can be said that, though the PM$_{10}$ concentration in the stay-at-home...
Fig. 7. Monthly change in concentrations (%) of six air pollutants with respect to previous year (A) PM$_{2.5}$, (B) PM$_{10}$, (C) NO$_2$, (D) CO, (E) SO$_2$, and (F) O$_3$. The missing months of CO and SO$_2$ are due to the lack of data.

period in 2020 is higher than the respective period in 2019, it could be much higher without stay-at-home order. The difference in the impact of COVID-19 on the concentration of these six air pollutants may occur due to these pollutants’ source differences. Temperature and other weather conditions may also be responsible for this discrepancy.

The spatio-temporal analysis also revealed nearly similar results with very few exceptions. There was notable spatial variation in PM$_{2.5}$, NO$_2$, and O$_3$ concentrations in all three periods in all three years. The Chicago airport area and the densely populated downtown of the city were predominately higher concentration zones for NO$_2$. The Eastern part of the city was observed as a high concentration area for O$_3$. The southwest industrial part of the city was always high PM$_{2.5}$ concentration area in all periods in all three years except the stay-at-home period in 2020. This variation indicates that the closure of industries contributed to reducing PM$_{2.5}$ concentration. In general, NO$_2$ was lower in the lower middle part of the city, where population density is comparatively lower.

In conclusion, it can be said that reduced human activities contributed to improving air quality.
by reducing some air pollutants, especially PM$_{2.5}$, NO$_2$, and CO. However, this improvement was transitory, and it reverted in the post-COVID era. Therefore, policies should be formulated and practiced to improve air quality for the long term, especially when it is proven that exposure to air pollution may cause major harmful health effects.

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