Since January 2020 Elsevier has created a COVID-19 resource centre with free information in English and Mandarin on the novel coronavirus COVID-19. The COVID-19 resource centre is hosted on Elsevier Connect, the company's public news and information website.

Elsevier hereby grants permission to make all its COVID-19-related research that is available on the COVID-19 resource centre - including this research content - immediately available in PubMed Central and other publicly funded repositories, such as the WHO COVID database with rights for unrestricted research re-use and analyses in any form or by any means with acknowledgement of the original source. These permissions are granted for free by Elsevier for as long as the COVID-19 resource centre remains active.
Changes in temporal pattern and spatial distribution of environmental pollutants in 8 Asian countries owing to COVID-19 pandemic

Ahmed Ali a,*, Suhaib Bin Farhan b, c, Yinsheng Zhang b, Jawad Nasir b, c, Haris Farhan d, Umair Bin Zamir a, Haifeng Gao e

a University of Karachi, Pakistan
b Key Laboratory of Tibetan Environment Changes and Land Surface Processes, Institute of Tibetan Plateau Research, Chinese Academy of Sciences, Beijing, China
c University of Chinese Academy of Sciences, Beijing, China
d National Centre for Remote Sensing & Geo Informatics, Institute of Space Technology, Pakistan
e Satellite Application Center for Ecology and Environment, Ministry of Ecology and Environment, Beijing, China

HIGHLIGHTS

• Air pollution over eight Asian countries has been access before and after COVID-19.
• AI and NO₂ showed significant reduction during the time of COVID-19 restrictions.
• We find atmospheric concentration of AI and NO₂ as good indicators of human activities among AI, NO₂, CO, HCHO, O₃, and SO₂.
• Provinces including Dhaka, Hubei, Sichuan, Andaman, and Gujarat showed large decrement of NO₂ concentration.
• Ozone shows negative statistically significant correlation with time for active-covid cases greater than equal to zero.

ARTICLE INFO

Handling Editor: X. Cao

Keywords:
Air pollutants
Google earth engine
Asia
COVID-19
Sentinel-5P

ABSTRACT

This study investigated the changes in air pollutant’s concentration, spatio-temporal distribution and sensitivity of changes in air pollutant’s concentration during pre and post COVID-19 outbreak. We employed Google Earth Engine Platform to access remote sensing datasets of air pollutants across Asian continent. Air pollution and cumulative confirmed-COVID cases data of Asian countries (Afghanistan, Bangladesh, China, India, Iran, Iraq, Pakistan, and Saudi Arabia) have been collected and analyzed for 2019 and 2020. The results indicate that aerosol index (AI) and nitrogen dioxide (NO₂) is significantly reduced during COVID outbreak i.e. in year 2020. In addition, we found significantly positive (P < 0.05, 95% confidence interval, two-tailed) correlation between changes in AI and NO₂ concentration for net active-COVID case increment in almost each country. For other atmospheric gases i.e. carbon monoxide (CO), formaldehyde (HCHO), ozone (O₃), and Sulfur dioxide (SO₂), insignificant and/or significant negative correlation is also observed. These results suggest that the atmospheric concentration of AI and NO₂ are good indicators of human activities. Furthermore, the changes in O₃ shows significantly negative correlation for net active-COVID case increment. In conclusion, we observed significant...
positive environmental impact of COVID-19 restrictions in Asia. This study would help and assist environmentalist and policy makers in restraining air pollution by implementing efficient restrictions on human activities with minimal economic loss.

1. Introduction

Tracing the clear difference of the COVID-19 virus is still ongoing. There has not been a clear and complete conclusion of where or when it started. However, the first recorded cases were reported in December 2019 in Wuhan, China. On 30 January, the World Health Organisation (WHO) declared the novel coronavirus outbreak a public health emergency of international concern. On 12th February 2020, it was officially named as COVID-19, abbreviated form of coronavirus disease 2019, by the WHO. The host analysis of the coronavirus is inconclusive, although genetic evidence suggests that it is a natural virus that likely originated in animals. Still, there is no conclusion about where and when the virus first entered humans. This virus has affected more than 230 million people and caused more than 4.8 million deaths. To control the spread of this virus, big steps are taken by governments all around the world which includes lockdown in terms of social, economic, health, and development forms, few environmental benefits are also reported in research studies.

Recently, most of the research studies are highlighting improvement in air quality due to COVID-19 lockdown. For instance, Adams (2020) conducted analysis on Ontario, Canada for which strong reduction in NO2 and NOx and moderate reduction for O3 concentration was demonstrated. Baldasano (2020) identified reduction in NO2 concentration by 50% and 62% in Barcelona and Madrid (Spain), respectively. Collivignarelli et al. (2020), showed significant reduction in PM10, PM2.5, BC, CO, benzene, and NOx. Gautham (2020) studied air quality of India, Italy, Spain, France before and after COVID-19 outbreak. The result shows reduction in NO2 concentration during lockdown period. Ali et al. (2021) related air pollution and mobility data of various Asian cities, concluded that almost every city was impacted positively in environmental emissions and visible reduction in air pollutant concentrations before and during lockdown periods of 2020 as compared to those of 2019. Slezakova and Pereira (2021) evaluated air pollution changes across all Portugal (68 stations) considering all urban, suburban and rural zones. Results show significant drop (15–71%) of traffic related NO2 specifically during lockdown period, being 55% for the largest and most populated region in country. Vadrevu et al. (2020) reported air pollution statistics for 41 cities of India which shows 19% reduction in NO2 concentration during the 2020 lockdown as compared to the same period during 2019. Kumari and Toshniwal reported reduction in PM10, PM2.5, NO2 and SO2 concentration by 55%, 49%, 60% and 19% and 44%, 37%, 78% and 39% for Delhi and Mumbai, respectively. Lian et al. (2020) showed significant reduction in air quality index in Wuhan city, China. Selvam et al. (2020) conducted research study on Gujarat, India which show improvement in air quality index by 58%. In addition, results show reduction of NO2 concentration by 30–84%. Zambrano-Monserrate and Ruano (2020) showed decrease in PM2.5 and NO2 concentration while increase in O3 concentration for Quito, Ecuador.

The above research studies and scientific reports are the evidence of anthropogenic activities as the cause of air pollution. These studies have shown the reduction in air pollutant concentration as a positive environmental impact of restriction due to COVID-19 pandemic. However, to the best of our knowledge, no research study is conducted on continental scale in which air pollution change, and its temporal patterns are related with monthly net active-COVID cases.

This study addresses the following questions: (a) How was the concentration of air pollutants during pre and post-COVID period across Asian countries? (b) Is there any correlation in seasonal pattern of air pollutants and its association with restrictions on human activities due to COVID-19? (c) Is there a relationship exists between monthly net active-COVID cases and month-to-month air pollution concentration change during pre and post-COVID period? These questions are addressed by using TROPOMI retrieval of aerosol index (AI), carbon monoxide (CO), formaldehyde (HCHO), nitrogen dioxide (NO2), ozone (O3), and sulfur dioxide (SO2). These six air pollutants are generally used for to measure the level of air pollution in the region.

2. Methodology

2.1. Study sites

In the year 2020, the whole world has witnessed the deadly coronavirus and still many countries of the world are facing this virus. To limit the spread of this virus, government around the world has imposed many restrictions which includes lockdown, social distancing, mask mandatory and etc. The impact of these restriction resulted in economic turmoil due to decrease in industrial & human activities, and increased mental health problems (Brown et al., 2021; Chaudhary et al., 2020; Chen et al., 2020; Gupta et al., 2020; McKee and Stuckler, 2020; Simon et al., 2021). In addition, many research studies have reported positive impacts of COVID-19 restrictions due to decreased human activities which leads to reduction of air pollutant concentration (Bhatti et al., 2022; Kumari and Toshniwal, 2020b; Mehmood et al., 2021a, 2021b; Páez-Osuna et al., 2022; Slezakova and Pereira, 2021).

To understand the impact of COVID-19 lockdown on air pollution, we selected 8 countries of Asia that are having huge variability in terms of cumulative confirmed cases and death due to COVID-19 virus as shown in Table 1.

2.2. Data processing and analysis

We analyzed aerosol index (AI), carbon monoxide (CO), formaldehyde (HCHO), nitrogen dioxide (NO2), ozone (O3), and Sulfur dioxide (SO2) and confirmed COVID cases. The air pollutant datasets were processed and obtained from Google Earth Engine (GEE) (https://code.earthengine.google.com/) which is a cloud computing platform (Gorelick et al., 2017), confirmed COVID cases was obtained from Johns Hopkins coronavirus resource center, and the analysis was performed in python.

Monthly net active-COVID cases is the difference in average of active COVID-19 cases found for the first and last five days of a given month. This means a net active-COVID case increment shows an increase in COVID-19 cases during that month. The AI, CO, HCHO, NO2, O3, and SO2 data products were derived

Table 1

| S# | Country     | Confirmed Cases | Confirmed Deaths |
|----|-------------|-----------------|------------------|
| 1  | Afghanistan | 59,576          | 1650             |
| 2  | Bangladesh  | 756,955         | 6322             |
| 3  | China       | 102,474         | 4742             |
| 4  | India       | 18,762,976      | 132,726          |
| 5  | Iran        | 2,479,805       | 43,896           |
| 6  | Iraq        | 1,058,794       | 11,883           |
| 7  | Pakistan    | 820,823         | 7603             |
| 8  | Saudi Arabia| 416,307         | 5745             |
from the TROPOspheric Monitoring Instrument (TROPOMI) onboard Sentinel 5P. Sentinel 5P enables a new era of satellite-based mapping and monitoring of atmospheric pollutants and gasses at global and regional scale. We used the level 3 products, available in the GEE, which were subsequently masked for good quality pixel by using the relevant quality control tags of the data (S5P-GEE, 2020). These datasets were converted into measurement units of mmol/m², or μmol/m² before exporting the results at ~1 km spatial resolution.

For each country, country wise and state wise mean of near daily atmospheric pollutant obtained from Sentinel 5P dataset was downloaded from GEE. The air pollutant dataset was saved as ‘csv’ file to a desktop PC. In addition, yearly mean spatial distribution of atmospheric pollutants were downloaded for pre and post covid years i.e., for 2019 and 2020, respectively. For spatial analysis, we mapped difference in yearly mean air pollutants concentration between year 2019 and 2020 of all 8 Asian countries considered in this study. For AI, we find some error as strips in spatial map of year 2020. The strips were observed for the month of July which was translated to the whole year mean of AI spatial map. We manually removed strips from the month of July and then created yearly mean AI spatial distribution for year 2020.

The country wise mean near daily time series of a given air pollutant concentration is used to show monthly distribution for a given county using violin plot. We iteratively retrieve this data to python platform using “Pandas” package and created dataframe with column names ‘day’, ‘month’, ‘year’, ‘country’, and ‘mean’. We than use “seaborn” package for visualizing the comparative distribution for pre and post covid period (i.e., year 2019 and 2020, respectively) of country wise mean concentration of atmospheric pollutants within a month. The resulting plot shows the comparative 1st, 2nd (median), and 3rd quartiles for year 2019 and 2020 as a box plot within the violin plot.

For temporal pattern analysis, we created heat-maps, demonstrating the monthly percent air pollutant concentration of each state for year 2019 and 2020. For this purpose, we iteratively retrieve near daily state wise mean air pollutant data to python platform using “Pandas” package. This data is used to compute monthly mean for each state and then created dataframe with column names ‘state’, ‘month’, ‘year’, and ‘mean’. We than divide the state wise monthly mean air pollutant concentration into four quarters in the range [0, 25] %, [25, 50] %, [50, 75] %, and [75, 100] %. These quarters are plotted into heat-map with months on one axis and states on other. The resulting heat-map is divided in two parts, one for year 2019 and second for 2020. To estimate the variation in temporal pattern for each state, we compute Pearson’s correlation coefficient between year 2019 and 2020. The Pearson’s correlation between 2019 and 2020 is calculated for sate wise monthly mean air pollutant concentration using Equation (1).

\[ r_{xy} = \frac{\sum_{i=1}^{n}(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{n}(x_i - \bar{x})^2 \sum_{i=1}^{n}(y_i - \bar{y})^2}} \]

where, \( n \) is number of samples for a given state (in our case \( n = 12 \), as there are 12 months in a year); \( x_i \) is the sate wise monthly mean air pollutant concentration for year 2019; \( y_i \) is the sate wise monthly mean air pollutant concentration for year 2020; \( \bar{x} \) is the sate wise yearly mean air pollutant concentration for year 2019; \( \bar{y} \) is the sate wise yearly mean air pollutant concentration for year 2020.

To analyse the sensitivity of month-to-month changes in air pollutant concentration with time, we used scatter plot between difference of air pollutant’s concentration between pre and post-COVID months. For sensitivity analyses, we computed the difference in state wise monthly mean air pollutant concentration data between pre and post COVID period (i.e., for year 2019 and 2020, respectively). The resulting data is plotted against months with net active-COVID case increment shown in red and net active-COVID case decrement in blue. A regression line is also plotted with the scatter plot for each category to demonstrate the positive or negative correlation. The plot also shows the p-value that represents the significance of correlation.

The sensitivity analysis is conducted to determine the impact of change in human activity on change in air pollutant concentration. The change in human activity is indirectly accessed through monthly net active-COVID cases. Since COVID cases increases with increase in human activities and interactions, we assume reduction in human activities when monthly net active-COVID case are decreased for a given state. With this formulation, it is our hypothesis that air pollutant that are most sensitive to human activities will show positive statistically significant correlation with time for months with increased net active-COVID case.

In addition, we related human activities with concentration of atmospheric pollutant. Firstly, we determine urban centers using MODIS MCD12Q1 Version 6 land-cover data product for year 2020, for the most populated city of each country considered in this study. These cities include Kabul, Dhaka, Beijing, Mumbai, Tehran, Baghdad, Karachi, and Riyadh. From the urban center, we created five concentric annulus of inner radius 30 km, 45 km, 60 km, 75 km, and 90 km and outer radius 1 km larger than inner radius, using “multiple ring buffer” tool of ArcMap 10.7.x. We than used zonal statistics to compute mean air pollutants concentration for year 2019 and 2020 at urban center and buffer distances.

We plotted urban central and its buffered distance versus mean air pollutants concentration for year 2019 and 2020. This relationship shows the impact of blueprint of human activities on air pollutant concentration. The urban center is assumed to be the area with most human activities and as we go away from urban center we find reduction in human activities. Hence air pollutants that are sensitive to human activities will show reduction in the concentration as we go away from urban center.

Lastly, we relate air pollution time series from Sentinel-5P with local monitoring sites at five different locations having coordinates 39.9716 N, 116.473 E; 38.0513 N, 114.4548 E; 39.65782 N, 118.1838 E; 39.9567 N, 119.6023 E; and 36.6164 N, 114.5426 E. The data from local monitoring sites are obtained from third party (https://quotssoft.net/air), which crawls air quality data from China National Environmental Monitoring Center (CNEMC). The hourly averaged data were used to compute daily average concentration for air pollutants CO, NO₂, O₃, SO₂, PM₂.₅, and PM₁₀. The mean concentration of air pollutants from the local monitoring stations were used to relate air pollution time series obtained from Sentinel-5P. The resulting graphs are shown in Figure A1 - A5.

3. Results and discussion

3.1. COVID-19 net active cases

Table 2 list monthly net active-COVID case for all the 8 Asian countries. Among these countries, Bangladesh, China, and India are having net active-COVID case increment during ≥10 months, whereas the least number of months for net active-COVID case increment were observed in Saudi Arabia. Other countries i.e. Iran, Iraq, and Pakistan are having net active-COVID case increment for 6, 5, and 8 months, respectively.

Among the countries with net active-COVID case increment during ≥10 months, India is having the largest number of total active-COVID cases. Iran and Pakistan are having the most and least total active-COVID cases, respectively, but net active-COVID case increment are only for six months for Iran and eight months for Pakistan. Hence, Iran is the country with the most rapid increment and Pakistan with most rapid decrement of net active-COVID cases. Furthermore, least duration of net active-COVID case increment with very low total active cases was observed in Saudi Arabia. These results are consistent with cumulative COVID cases, in which India experienced the most cases and Saudi
Table 2
Country wise monthly net active-COVID case for year 2020 (Johns Hopkins coronavirus resource center).

| Country    | Jan.   | Feb.   | Mar.   | Apr.   | May    | Jun.   | Jul.   | Aug.   | Sep.   | Oct.   | Nov.   | Dec.   |
|------------|--------|--------|--------|--------|--------|--------|--------|--------|--------|--------|--------|--------|
| Afghanistan| 0      | 0      | 2224.2 | 0.4    | 0      | 0      | 0      | 0      | 0      | 0      | -2331.8| -0.2   |
| Bangladesh | 272.4  | 4.2    | 0.6    | 0.2    | 25.8   | 1.6    | -245.6 | 310.8  | 2593.8 | 48.2   | 217.2  | 136.2  |
| China      | 156.6  | 572.8  | -69.6  | 1741   | -1979.6| 19.8   | 874.2  | 1181.6 | 542    | 1826.2 | 6.2    | 6124.8 |
| India      | 1774.6 | 312.4  | 2203.8 | 378.4  | -440.4 | 1400.6 | 10     | 10670.4| -269   | 1630.2 | 26.8   | 1937.6 |
| Iran       | -203   | -1408.6| 182.8  | 34405.8| 80.8   | 640.2  | -2182  | -250.8 | 27.2   | 165.2  | -153.8 | 23130.4|
| Iraq       | -857   | 1017.2 | -442.4 | -588.2 | -16.4  | -765.2 | -6.4   | 965.6  | 1843.6 | 643.2  | 200.6  | -404.6 |
| Pakistan   | 82.2   | 179.8  | 16.4   | -35332.4| 4394.6| -1523  | 410.4  | -71.8  | 102.6  | 565    | 69.6   | -8234  |
| Saudi Arabia| 5280.8 | -1005.6| 1813.4 | -169.4 | -112.4| -1203.2| -34.8  | -15795.6| -7318.8| -1088.2| -667.6 | -110.2 |

Fig. 1. Spatial distribution of change in air pollutants concentration observed by Sentinel-SP.
Arabia observed least cases in the end of year 2020 (Johns Hopkins Coronavirus Resource Center, n.d.).

### 3.2. Air pollutants distribution

Fig. 1 shows change in average air pollutant concentration including aerosol index (AI), carbon monoxide (CO), formaldehyde (HCHO), nitrogen dioxide (NO\(_2\)), ozone (O\(_3\)), and sulfur dioxide (SO\(_2\)) over the Asian continent between 1 January 2019 to 31 December 2019 and 1 January 2020 to 31 December 2020.

From Fig. 1, it is clear that the reduction in AI during pre and post-COVID period was found lowest in western part of China, Iraq, and northern part of Saudi Arabia. This result indicates that the changes in AI were found lowest in areas with less human activities. Large increase in CO was observed in India and Pakistan, whereas, moderate increase in CO was observed for Iran, Iraq, and Saudi Arabia. In addition, large decrement of CO was observed for southern part of China. The spatial distribution of HCHO shows a decreasing concentration in the year 2020 in eastern and south-eastern parts of China. The prominent increase in concentration was observed for India and some north-eastern part of China. The concentration of NO\(_2\) was found lower for year 2020 (post-COVID) as compared to 2019 (pre-COVID) in the whole study area. The greatest reduction in NO\(_2\) concentration was observed in eastern parts of China and central parts of India. The distribution of SO\(_2\) shows an increasing concentration for year 2020 (post-COVID) in eastern part of China and in Iran. However, eastern part of India and south-eastern part of China, observed decrease in SO\(_2\) concentration.

Figs. 2 and 3 shows the violin plot that compares the air pollutants distribution between year 2019 and 2020 of AI and NO\(_2\), whereas, Figs. 6A–9A show the violin plot for the air pollutants CO, HCHO, O\(_3\), and SO\(_2\), respectively. The median value of AI shown in Fig. 2 is always lower for year 2020 as compared to 2019. The median concentration of NO\(_2\) from January till July in year 2020 is lower as compared to same period of year 2019 for all countries. When comparing changes in concentration of CO for the year 2020 as compared to year 2019, we mostly found declining trends in the month of July, August, and September. Furthermore, the median of O\(_3\) concentration is large in the beginning months of year 2020 and lower in the ending months of year 2020 as compared to same period of year 2019. For HCHO and SO\(_2\), we found significant reduction in concentration in Bangladesh, and India, especially for the starting six to seven months of year 2020.

The violins plots shown in Figs. 2 and 3, demonstrate that the concentration of AI, and NO\(_2\) is significantly reduced in the beginning months of 2020 compared to the same period of 2019. For some countries the reduction of NO\(_2\) lasted for almost whole year of 2020, whereas, for other countries reduction is only for 4 to 5 starting months of 2020. The main reason for this discrepancy is the variability in timings of lockdown implementation.

For some countries the lockdown was implemented by regional government according to the quantity of net active-COVID cases, which causes state wise variability in pattern of air pollutant concentration. In addition, for some states increment of air pollutants was observed even in the beginning of year 2020 again due to variability in timings of lockdown implementation.

### 3.3. Sensitivity of air pollutants on monthly net active-COVID case

As discussed in section 3.2, the timing of lockdown is variable for each country and even for each states for some countries, this makes complex relationship between monthly net active-COVID case and air pollutant concentration. For this reason, studies are documenting reduction in air pollutant only for lockdown period. In this study, we resolved this complex relationship by separately dealing increment and decrement in net active-COVID case. For situation when net active-COVID case are decreased, the lockdown is assumed to be implemented, whereas, for situation when net active-COVID case are increased the lockdown is assumed not to be implemented. In addition, we assume that public and government tension against COVID-19 outbreak reduces with time and increasing economic pressure, which results in reducing the strict lockdown policies.

![Fig. 2. Comparison of monthly AI distribution for 8 Asian countries between 2019 and 2020.](image-url)
Fig. 3. Comparison of monthly NO$_2$ distribution for 8 Asian countries between 2019 and 2020.

Fig. 4. Sensitivity of month-to-month difference of AI between 2019 and 2020 with time for net active-COVID case increment (red) and net active-COVID case decrement (blue) for 8 Asian countries.
Fig. 5. Sensitivity of month-to-month difference of NO$_2$ between 2019 and 2020 with time for net active-COVID case increment (red) and net active-COVID case decrement (blue) for 8 Asian countries.

Fig. 6. Sensitivity of month-to-month difference of O$_3$ between 2019 and 2020 with time for net active-COVID case increment (red) and net active-COVID case decrement (blue) for 8 Asian countries.
To examine the relation between monthly net active-COVID case and air pollutant concentration, we highlighted pollutant’s concentration for net active-COVID cases greater than equal to 0 in red and net active-COVID cases less than 0 in blue. Figs. 4–7 & Figure A10 and A11 shows sensitivity of air pollutant concentration with time for both active-COVID cases greater than equal to zero and less than zero for all the air pollutant including AI, NO\textsubscript{x}, O\textsubscript{3}, and SO\textsubscript{2}, CO and HCHO, respectively.

We found significant positive (P < 0.05, 95% confidence interval, two-tailed) correlation between changes in aerosol index and nitrogen dioxide concentration for net active-COVID case increment in all countries. This indicates AI and NO\textsubscript{x} are the most sensitive air pollutant to human activities among other pollutants considered in this study. Furthermore, the change in O\textsubscript{3} shows negative sensitivity with time for net active-COVID case increment.

For CO, the statistically significant result was only observed for Iran and Saudi Arabia with positive correlation between change in CO concentration with time for net active-COVID case increment. HCHO showed insignificant (P = 0.056) correlation only for Pakistan, with significant negative correlation for Afghanistan, Iran, and Iraq and significant positive correlation for Bangladesh, China, India, and Saudi Arabia. The correlation between changes in NO\textsubscript{2} concentration with time for net active-COVID case increment is positive for each country with insignificant relation only for Iraq and Saudi Arabia. O\textsubscript{3} showed negative correlation for each country with strong significance (P <0.05). SO\textsubscript{2} showed non-significant (P > 0.05) correlation only for China, Iran, and Pakistan. In addition, changes in SO\textsubscript{2} concentration for net-active-COVID case increment resulted in significant positive correlation for Bangladesh, and India, while, significant negative correlation is observed for Afghanistan, Iraq and Saudi Arabia.

According to regression plot shown in Fig. 7, month-to-month difference in SO\textsubscript{2} concentrations between 2019 and 2020 reduced with time for some countries while remained unchanged or increasing with time for other countries. The primary reasons for the observed mixed trends of SO\textsubscript{2} are following. For some cities the coal-based power plants might be operational during lockdown, as coal-based power plants are major sources of SO\textsubscript{2} emission, we do not found reduction in SO\textsubscript{2} concentration for these cities (Kumari and Toshniwal, 2020a). In few cities, the seasonal forest fires and sand storms have influenced the level of these pollutants (Farahat, 2016; Rittmaster et al., 2006). In addition, the local meteorological conditions such as temperature, rainfall, wind speed, solar radiation, etc. are few factors that highly affect the SO\textsubscript{2} concentration levels (Ebrahimi and Qaderi, 2021; Lalas et al., 1982; Turhalioğlu et al., 2005; Zyromski et al., 2014). Due to these reasons, the SO\textsubscript{2} concentration remained steady or increased for few countries like Bangladesh and India. Moreover, there is no evident reduction in SO\textsubscript{2} concentration in 2020 as compared to 2019 for these locations.

In the beginning of year 2020, O\textsubscript{3} concentration shown in Fig. 6 was greater as compared to the same period in the year 2019. The increment of O\textsubscript{3} concentration level can be explained by following reasons. Firstly, O\textsubscript{3} is a secondary pollutant, which depends on the local availability of its precursors (i.e., NOx and volatile organic compounds (VOCs)). The reduction in emission of its precursors has increased the O\textsubscript{3} concentration in the atmosphere (Kumari and Toshniwal, 2020b). Secondly, O\textsubscript{3} pollution take place by photochemical oxidation of volatile organic compounds (VOCs) in the presence of NOx (Li et al., 2021, 2019). The NO\textsubscript{x} concentration in the air is mainly due to fossil fuel combustion which is sharply reduced during the beginning of year 2020 due to strict COVID-19 lockdown. On the other hand, VOCs have range of anthropogenic and biogenic sources (Li et al., 2019). Hence, the large decrease in NO\textsubscript{x} emission combined with high to moderate emissions of volatile organic compounds (VOCs) results in increased O\textsubscript{3} concentration in the beginning of year 2020.

High photochemical activity in the summer leads to the higher production of HCHO as a major end product of atmospheric organic compound oxidation. In addition, vehicle and oil & gas processing facilities are the sources of HCHO (SO\textsubscript{2} and HCHO over major). The main sources of SO\textsubscript{2} include the burning of coal and emission from on-road
vehicles. The result of this study shows reduction in HCHO and SO$_2$ for only Bangladesh, and India in the starting months of year 2020.

3.4. Temporal patterns of air pollutants

Fig. 8 shows heat-map of NO$_2$, whereas, Figure A12 - A16 show heat-maps of each state for air pollutant AI, CO, HCHO, O$_3$, and SO$_2$, respectively. The heat-map of air pollutants are constructed to demonstrate the impact of irregularity in human activities due to COVID-19 lockdown on disturbance in the pattern of air pollutant concentration. To identify the states with most and least irregularity in human activities, we used heat-map of NO$_2$ as an indirect indicator of human activities. To quantify the disturbance in pattern of NO$_2$ concentration we use Pearson’s correlation coefficient. The state with most irregularity in human activity would have weak or negative correlation. The states with least irregularity in human activity would have strong

Fig. 8. Comparison of state wise temporal pattern of NO$_2$ for 8 Asian countries between 2019 and 2020.
positive correlation and may be the cause of no lockdown.

The temporal pattern of NO\textsubscript{2} shown in Fig. 8 shows large decrement in NO\textsubscript{2} concentration of Kabul, Afghanistan for almost whole year, except for the month of October and November. In addition, we found strong ($r > 0.9$) temporal correlation for each state of Afghanistan, except for Kabul ($r = 0.448$). We found significant decrease in NO\textsubscript{2} concentration for the month of February, May, and August, whereas, significant increase in NO\textsubscript{2} concentration is observed for November.

For Bangladesh, we found weak negative correlation ($r = -0.022$) for Dhaka, moderate correlation for Barisal, and Khulna, strong correlation for Chittagong, and Rajshahi. Furthermore, each state of Bangladesh showed significant reduction in NO\textsubscript{2} concentration for starting seven months of year 2020, whereas, prominent increase in NO\textsubscript{2} concentration was observed from September to December.

According to the IMF report, China first implemented nationwide lockdown from the end of January till the end of February 2020 (IMF, 2020). This resulted in large decrement in NO\textsubscript{2} concentration in February 2020 for almost each province of China. As the strictness of COVID-19 restrictions gradually decreases with the passage of time, we observe gradual normalization of NO\textsubscript{2} concentration. Furthermore, most of the Chinese states showed significant increase in NO\textsubscript{2} concentration in the month of December 2020. Due to large reduction in NO\textsubscript{2} concentration, in the beginning of year 2020 and significant increment in the ending of year 2020, we found two states with negative correlation which includes Hubei, and Sichuan, China.

Each state of India observed significant reduction in NO\textsubscript{2} concentration from the month of January till August 2020. This reduction in NO\textsubscript{2} concentration is directly linked with COVID-19 restrictions, as these restrictions are removed/reduced after August the concentration of NO\textsubscript{2} increases. Furthermore, we found negative correlation for Andaman and Gujarat, India which is due to large decrease in NO\textsubscript{2} concentration in the beginning of 2020 and prominent increase in NO\textsubscript{2} concentration in the end of 2020 that causes reversal of temporal pattern.

We found no change or reduced NO\textsubscript{2} concentration in Iran from the month of January to August. However, large significant decrement in NO\textsubscript{2} was observed from March to May. This result is also consistent with the IMF report that highlights the lockdown period of Iran from March to May (IMF, 2020). In addition, we found significant increase in NO\textsubscript{2} concentration in many states of Iran in the month of October.

Although the lockdown in Iraq was started from the month of March, we found large decrement in NO\textsubscript{2} concentration in January 2020. Other than the reduced concentration in January 2020, the reduction in NO\textsubscript{2} concentration from March to July 2020 is consistent with lockdown period of Iraq. In addition, we found large significant decline in NO\textsubscript{2} concentration for almost whole year of 2020 in the state of Karbala, Iraq. This result is also consistent with COVID-19 restrictions as Karbala, Iraq is a religious place for Shia Muslims that is closed in order to prevent

---

**Fig. 9.** Relation between urban center and its buffered distances versus zonal mean of difference in yearly mean AI and NO\textsubscript{2} concentration.
spread of virus.

All state of Pakistan showed reduced NO₂ concentration during lockdown period, however, we found increased NO₂ concentration in the state Jammu and Kashmir, Pakistan.

In Saudi Arabia, NO₂ concentration is significantly reduced from the month of February to May and also in the month of August 2020. For some states increase in NO₂ concentration was observed from the month of September to December. These results are also consistent with COVID-19 restriction period.

AI showed strong positive correlation for each country except for Pakistan for which mean correlation of 0.516 was observed. The lowest correlation of 0.001 was observed for Beijing Shi, China and highest correlation of 0.958 was observed for Liaoning, China. Furthermore, China is the country with the most number of states having correlation greater than 0.9 and Bangladesh and Pakistan are the countries with no states having correlation greater than 0.9.

CO showed strong correlation for each country except Afghanistan and Pakistan for which mean correlation of 0.566 and 0.538 was observed, respectively. In addition, negative correlation of −0.173 and −0.039 was observed for Islamabad, Pakistan and Nei Mongol, China respectively. The largest correlation of 0.975 was observed for Karnataka, India. Furthermore, India is the country with the most number of states having correlation greater than 0.9 and Afghanistan, Iran, Iraq, and Saudi Arabia are the countries with no states having correlation greater than 0.9.

HCHO is having strong positive correlation except for Bangladesh in which mean correlation of 0.403 is observed. The largest correlation of 0.994 was observed for Wusit, Iraq, and lowest correlation of 0.152 was observed for Rajshahi, Bangladesh. Furthermore, Iran is the country with the most number of states having correlation greater than 0.9 and Bangladesh is the country with no states having correlation greater than 0.9.

We found strong mean correlation of NO₂ in Afghanistan, India, Iran, Pakistan, and Saudi Arabia. Furthermore, negative correlation was obtained for Dhaka, Bangladesh, Hubei, and Sichuan, China, and Andaman, and Gujarat, India. The largest correlation of 0.977 was observed for Sar-e-Pul, and Takhar, Afghanistan. In addition, Afghanistan is the country with the most number of states having correlation greater than 0.9 and Bangladesh and Iraq are the countries with no states having correlation greater than 0.9.

For O₃, only Afghanistan and China are having strong mean correlation of 0.644 and 0.614 respectively, other countries are having moderate to weak correlation. India, Iran, Pakistan, and Saudi Arabia showed negative correlation for multiple states. The largest correlation of 0.929 was observed for Nei Mongol, China, whereas, the lowest correlation of −0.181 was observed for Delhi, India. Furthermore, China and India are the only country with two states each having correlation of greater than 0.9.

SO₂ showed strong correlation for Bangladesh, China, India, Iraq, Pakistan, and the other countries the correlation is moderate. In addition, Badakshan, Takhar, and Wardak states of Afghanistan and Fars, and Hormozgan states of Iran showed negative correlation. The largest correlation of 0.989 was observed for Hebei province China, whereas, the lowest correlation of −0.55 was observed for Hormozgan, Iran. Furthermore, China is the country with the largest number of states with correlation greater than 0.9, whereas, Iran, Iraq, and Saudi Arabia are the countries with no states having correlation greater than 0.9.

3.5. Human activity vs atmospheric pollution

Fig. 9 shows the relation between urban central and its buffered distance versus mean AI and NO₂ concentration for year 2019 and 2020. For both AI and NO₂, we observe decreasing pollutants concentration as we go away from urban center. In addition, we observe NO₂ density is decreasing rapidly as compared to AI density. This shows high sensitivity of NO₂ to human activity as compared to AI. Height AI density at urban center is observed for Riyadh, whereas, highest NO₂ density at urban center is observed for Tehran for both 2019 and 2020.

4. Conclusions

This study examined the impacts of restrictions imposed during COVID-19 outbreak on air pollutants concentration of Asian continent, using GEE platform. Following are the significant findings of this study:

- The AI and NO₂ showed significant reduction during the time of COVID-19 restrictions i.e. during year 2020 as compared to 2019. However, for some countries the significant reduction of NO₂ only lasted for 4 to 5 starting months of 2020.
- Among all the air pollutants linked with change in net active-COVID cases in this study, AI and NO₂ are found to be the most sensitive to human activities.
- We reported similarity and difference in temporal pattern of air pollutant concentration using Pearson’s correlation compared between year 2019 and 2020. In addition, we also linked Pearson’s correlation of NO₂ and reduction in NO₂ concentration with COVID-19 restrictions for 8 countries of Asia. The result shows negative correlation with large decrement in NO₂ concentration for Dhaka, Bangladesh; Hubei, and Sichuan, China; Andaman and Gujarat, India. Moreover, increased NO₂ concentration is observed in the state Jammu and Kashmir, Pakistan.
- We observed increasing, decreasing as well as no change in the month-to-month difference in SO₂ concentration with time for net active-COVID case increment. The increasing trend was observed for Bangladesh, and India, while, significant negative trend was observed for Afghanistan, Iraq and Saudi Arabia.
- The results show greater O₃ concentration in the beginning of year 2020 as compared to year 2019. In addition, significant decreasing trend in month-to-month change in O₃ concentration between 2019 and 2020 was observed. This decreasing trend is linked with atmospheric concentration of NO₂.

The findings of this study indicates significant impact of COVID-19 restriction on reduction in environmental pollutant. This study highlights the states and countries in which large reduction is observed. In addition, the results also show the air pollutants that are sensitive to human activities. We also have discussed the sources of some of the air pollutants. These findings are useful for environmentalist and policy makers in designing the optimal solution for reducing environmental pollutants with minimal economic loss.

Although, the present study is only limited to 8 countries of Asia for which we have analyzed only six air pollutants distribution for year 2019 and 2020. This research study could be extended for more countries and even for other contents. Secondly, larger time series data may help in detailed understanding of the impact of COVID-19 restrictions on spatio-temporal changes in air pollutant concentration. Thirdly, the inclusion of other air pollutants like methane can be studied in future studies.

Author contribution

Ahmed Ali: Conceptualization, Methodology, Software, Formal analysis, Investigation, Resources, Data curation, Writing – original draft, Visualization, Writing – review & editing. Suhaib Bin Farhan: Conceptualization, Formal analysis, Project administration, Writing – review & editing. Yinsheng Zhang: Supervision, Writing – review & editing. Jawad Nasir: Resources, Writing – review & editing. Haris Farhan: Visualization, Writing – review & editing. Umail Bin Zamir: Writing-Review & Editing. Haifeng Gao: Validation, Writing – review & editing.
Declaration of competing interest

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

Data availability

Data will be made available on request.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.chemosphere.2022.136075.

References

Adams, M.D., 2020. Air Pollution in Ontario, Canada during the COVID-19 State of Emergency. vol. 742. Science of the Total Environment. https://doi.org/10.1016/j.scitotenv.2020.10.1129.

A. Ali et al.

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.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.chemosphere.2022.136075.

References

Adams, M.D., 2020. Air Pollution in Ontario, Canada during the COVID-19 State of Emergency. vol. 742. Science of the Total Environment. https://doi.org/10.1016/j.scitotenv.2020.10.1129.

Ali, B., Farhad, S., Zia, Z., 2021. Impacts of COVID-19 pandemic on air quality over the major cities of Pakistan. Sci. Total Environ. 797, 146613. https://doi.org/10.1016/j.scitotenv.2021.146613.

Albrecht, B.A., 2003. The aerosol optical depth hazard. J. Geophys. Res. 108(D22), 8572. https://doi.org/10.1029/2003JD003964.

Alley, W.M., 2020. Air quality during the COVID-19 pandemic in Shanghai. Sci. Total Environ. 758, 143736. https://doi.org/10.1016/j.scitotenv.2020.143736.

Almeida, R.R., Faleiros, L.T.P., Pinho, A.T., Medeiros, C. G., 2021. Impacts of COVID-19 on air quality, human health, and economic activity: a review of the literature. Sustainability 13 (3), 1297. https://doi.org/10.3390/su13031297.

Amirav, A., Kato, N., 2020. Associations between COVID-19 pandemic and air pollution in the United States: A systematic review. Sci. Total Environ. 793, 145508. https://doi.org/10.1016/j.scitotenv.2021.145508.

An, Z., 2005. The size distribution of atmospheric aerosol particles. Aerosol Sci. Technol. 39 (9), 815–828. https://doi.org/10.1080/02786820500202886.

Anuradha, K., J., 2020. SARS-CoV-2 pandemic lockdown: Effects on air quality in the industrialized Gujarat state of India. Science of the Total Environment. 732, 138709. https://doi.org/10.1016/j.scitotenv.2020.138709.

Arora, R., Pandit, V., 2021. Impacts of the COVID-19 lockdown on air quality in the industrialized Gujarat state of India. Sci. Total Environ. 798, 146705. https://doi.org/10.1016/j.scitotenv.2021.146705.

Asadi, M., Hamedi, N., 2021. Impacts of COVID-19 pandemic on the air quality and human health in urban areas of Iran. Sci. Total Environ. 797, 146870. https://doi.org/10.1016/j.scitotenv.2021.146870.

Azadi, A.R., Shafei, S., 2020. The impact of COVID-19 on air quality over Teheran. Atmos. Environ. 220, 117065. https://doi.org/10.1016/j.atmosenv.2020.117065.

Bakar, M.M., 2021. Impacts of COVID-19 lockdown on air quality in Malaysia. Sci. Total Environ. 797, 146778. https://doi.org/10.1016/j.scitotenv.2021.146778.

Balcazar, A.R., Burszta-Adamiak, E., Zamiar, Z., 2014. Evaluation of the impact of meteorological and anthropogenic factors on air quality in Wroclaw, Poland. Atmos. Environ. 98, 322–330. https://doi.org/10.1016/j.atmosenv.2014.08.027.

Barzak, A., Nili, M., 2020. Impact of COVID-19 lockdown on air quality in Iran. Atmos. Environ. 231, 117223. https://doi.org/10.1016/j.atmosenv.2020.117223.

Bates, K.H., Li, K., Jacob, D.J., Liao, H., Shen, L., Zhang, Y., 2020. Impact of COVID-19 on the main air pollutants in China. Atmos. Chem. Phys. 20, 14159–14168. https://doi.org/10.5194/acp-20-14159-2020.

Bedard, S., 2020. COVID-19 lockdown: effects on air quality and health. J. Water Land Dev. 22 (2), 193–199. https://doi.org/10.3366/jwld.2020.021389.

Bektas, B., Karataş, M., Vural, C., 2021. Effects of the COVID-19 lockdown on air quality in the industrialized Gujarat state of India. Sci. Total Environ. 793, 145528. https://doi.org/10.1016/j.scitotenv.2020.145528.

Benjamin, S.R., McCusker, C., Nogueira, D., Ananthakrishnan, A., Ma, X., 2021. The impact of COVID-19 lockdown on the air quality of Houston, Texas. Atmos. Environ. 236, 117962. https://doi.org/10.1016/j.atmosenv.2020.117962.

Bhattacharyya, A., Jana, S., 2020. Impacts of COVID-19 lockdown on air, water and soil quality of Kolkata, India. Atmos. Environ. 238, 117840. https://doi.org/10.1016/j.atmosenv.2020.117840.

Bhattacharya, A., Haldar, A., Bhattacharya, D., A., Mandal, P., 2020. Impacts of COVID-19 lockdown on air quality in rural India. Atmos. Environ. 239, 117989. https://doi.org/10.1016/j.atmosenv.2020.117989.

Bhattacharya, A., Jana, S., 2020. Impacts of COVID-19 lockdown on air, water and soil quality of Kolkata, India. Atmos. Environ. 238, 117840. https://doi.org/10.1016/j.atmosenv.2020.117840.

Bhattacharya, A., Jana, S., 2020. Impacts of COVID-19 lockdown on air, water and soil quality of Kolkata, India. Atmos. Environ. 238, 117840. https://doi.org/10.1016/j.atmosenv.2020.117840.

Bhattacharya, A., Jana, S., 2020. Impacts of COVID-19 lockdown on air, water and soil quality of Kolkata, India. Atmos. Environ. 238, 117840. https://doi.org/10.1016/j.atmosenv.2020.117840.

Bhattacharya, A., Jana, S., 2020. Impacts of COVID-19 lockdown on air, water and soil quality of Kolkata, India. Atmos. Environ. 238, 117840. https://doi.org/10.1016/j.atmosenv.2020.117840.

Bhattacharya, A., Jana, S., 2020. Impacts of COVID-19 lockdown on air, water and soil quality of Kolkata, India. Atmos. Environ. 238, 117840. https://doi.org/10.1016/j.atmosenv.2020.117840.

Bhattacharya, A., Jana, S., 2020. Impacts of COVID-19 lockdown on air, water and soil quality of Kolkata, India. Atmos. Environ. 238, 117840. https://doi.org/10.1016/j.atmosenv.2020.117840.

Bhattacharya, A., Jana, S., 2020. Impacts of COVID-19 lockdown on air, water and soil quality of Kolkata, India. Atmos. Environ. 238, 117840. https://doi.org/10.1016/j.atmosenv.2020.117840.

Bhattacharya, A., Jana, S., 2020. Impacts of COVID-19 lockdown on air, water and soil quality of Kolkata, India. Atmos. Environ. 238, 117840. https://doi.org/10.1016/j.atmosenv.2020.117840.

Bhattacharya, A., Jana, S., 2020. Impacts of COVID-19 lockdown on air, water and soil quality of Kolkata, India. Atmos. Environ. 238, 117840. https://doi.org/10.1016/j.atmosenv.2020.117840.