Analyzing the spatio-temporal directions of air pollutants for the initial wave of Covid-19 epidemic over Bangladesh: Application of satellite imageries and Google Earth Engine

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ABSTRACT

One of the most critical issues for city viability and global health is air quality. The shutdown interval for the COVID-19 outbreaks has turned into an ecological experiment, allowing researchers to explore the influence of human/industrial operations on air quality. In this study, we have observed and examined the spatial pattern of air pollutants, specifically CO, NO_2, SO_2, O3 as well as AOD Over Bangladesh. For that reason, the timeline was chosen from March 2019 to October 2020 (before and during the first surge of COVID-19). The full analysis has been performed in Google Earth Engine (GEE). The findings showed that, CO, SO_2, and AOD levels dropped significantly, but SO_2 dropped slowly and O_3 levels were similar, with marginally greater quantities in some areas during the lockdown than in 2019. During the shutdown, the association involving airborne pollutants and weather parameters (temperature and rainfall) revealed that rainfall and temperature were directly associated with air pollutants. COVID-19 mortality had a high positive connection with NO_2 (R^2 = 0.145; r = 0.38) and AOD (R^2 = 0.17; r = 0.412). It is also found that various air impurities concentration has a strong relationship with Covid death. It would help the policymakers and officials to gain a better understanding of the sources of atmospheric emissions to develop a substantial proof of short- and long-term mitigation ways to enhance air quality and reduce the associated disease and disability burden.

1. Introduction

Air quality is one of the most serious and pressing issues in emerging nations (Sannino et al., 2021), and it has been triggered by increasing urbanization, the increase in trade, and the use of fossil energy in industrial and household events (Roy et al., 2020; Perera, 2017; Xu and Lin, 2017; He et al., 2017). Air is the primary element of environment and environment deterioration has now been a major issue at the national, continental, and global levels in the past few decades (Eckhoff, 2009). Pollution can be defined as negative alterations in the natural surroundings. Air pollution appears to be an unavoidable aspect of our lives (Agarwal et al., 2021). It not only burdens our civilization, but also harms soil, water, crop, plant, animals, habitats, and man-made structures, ultimately lowering

financial benefit, personal satisfaction, and well-being (Manisalidis et al., 2020). Air pollution is any meteorological state in which certain pollutants are available in such concentrations that they have an unfavorable influence on human being and his/her surroundings (Appannagari, 2017; Mehmood et al., 2022). When vast amounts of damaging materials or chemicals, such as gases, particulate matter, and biomolecules, enter the Earth's atmosphere, this is referred to as air contamination (Arya, 1999; Sannino et al., 2021). Carbon monoxide (CO), ozone (O_3), sulfur dioxide (SO_2), nitrogen dioxide (NO_2), and particulate matter (PM2.5 and PM10) are the most significant contaminants in the world's urban regions (Zhang et al., 2020). These contaminants are commonly generated by both fixed and mobile sources. Fixed resources include household, commercial, and industrial operations, whereas moveable sources of air pollution include transportation and automobiles that contaminate the air by emitting pollutants such as vehicle emissions and particulates (Islam and Chowdhury, 2021). In reality, autos emit the other pollutants significantly more frequently than any other source, with the exception of SO2, which is mostly generated by domestic and manufacturing sources. (Ghasempour et al., 2021).

An ideal alternative for long-term spatial and chronological examining of air quality at various scales is satellite-based remote sensing knowledge. (Aldabash et al., 2020). Satellite photography was first used to assess air quality in the 1970s. Since 1978, several forms of satellite imagery have been widely utilized to monitor the quality of the air (Ghasempour et al., 2021). Several scholars have examined the monitoring, analysis, and retrieving of air contaminants such as sprays, NO_2, SO_2, PMX, CH_2, CO, and O_3 utilizing remotely sensed satellites (Aldabash et al., 2020; de Laat et al., 2020; Feng et al., 2019; Hajiloo et al., 2019; Manisalidis et al., 2020; Wang et al., 2019).

A study in Italy, Germany, France, and Spain indicates long-term NO_2 intake is perhaps one of the major causes of COVID-19 fatalities in these areas (Ogen, 2020). There is a considerable relationship between the degree of human activity and the decrease in NO_2 levels (Mesas-Carrascosa et al., 2020). Another study found that atmospheric temperature decreased by 17% over India and 25% over China. Furthermore, a 17% drop in boundary layer SO_2 was recorded, particularly over India's eastern sector, while a 6.5% reduction in CO was found over north-central China (Metya et al., 2020). Researchers in Iran observed that the NO_2 and CO pollution levels were 5% fewer in 2020 (the initial year of the COVID-19 pandemic) than in 2019, demonstrating that isolation regulations were followed in addition to people's early panic of the coronavirus (Shami et al., 2022). According to another study (Muhammad et al., 2020), pollution has been decreased up to 30% in the COVID-19 hotspots, including Wuhan, Italy, Spain, and the United States for the unmovable situation (Nichol et al., 2020). Reported that Ozone Monitoring Instrument (OMI) satellite derived NO_2 declined dramatically throughout China in March and April 2020. They also reported that an increase in PM2.5, in contrast to the drop in NO_2 in BTH and throughout China, is most likely attributable to the increased creation of secondary particles. Between 2019 and 2020, there was a significant drop in pollution in Wuhan, with a decrease of around 83 percent, 11 percent, 71 percent, 4 percent, and 62 percent in NO_2, HCHO, SO_2, CO, and AOD, respectively (Ghahremanloo et al., 2021). (Ahmed et al., 2022) discovered a strong correlation between Bangladeshi climate variables and air quality measurements and daily new cases of COVID-19 (S. et al., 2020). found a slight increase in ozone (O3: 4%; 95% CI: 2–10%), a decrease in inhabitants-biased concentrations of surface nitrogen dioxide (NO2: 60% with 95% CI 48–72%), and a rise in fine particles (PM2.5: 31%; 95% CI: 17–45%) in 34 countries during shutdown dates up until May 15 (Kanniah et al., 2020). Found a significant drop in NO_2 across Southeast Asia during the shutdown period.

Bangladesh, the world's eighth-most populated country, with roughly 2.2 percent of the worldwide inhabitants and is a low-–middle-income country striving to combat disease spread (Qiu et al., 2021). The Bangladeshi government declared the very first incidence of COVID-19 in the country on March 7, 2020 (Anwar et al., 2020). The first rigorous shutdown began on March 26, 2020, and was later extended in several instances until May 30, 2020 (Monjur and Hassan, 2020). This blockade barred all modes of transit, including air, sea, and road travel, for both domestic and foreign travel. The shutdown, enacted to restrict the spreading, led to self-isolation, reduced outside actions, and the interruption and shutdown of shipping and manufacturing sectors. As a result, this pandemic-fighting method has altered pollution concentrations and notably helped to decrease in various emission sources (Kumar et al., 2020; S. et al., 2020).

Several investigations have been carried out to determine whether the region's general air quality has improved (Islam et al., 2021a). In some studies, only a particular city of Bangladesh is considered (Ahmed et al., 2022), some studies have only detected a change of a particular air pollutant (Rana et al., 2022), the relation between health hazards due to covid and air quality concentration (Roy et al., 2020) climatic impact on air quality (Faisal et al., 2022) are evaluated in some studies. However, none of these analyses focused into the comprehensive scenario of Bangladesh. Where various air pollutant concentration changes owing to lockdown, climatic and meteorological effects on air pollutants, and the relationship between covid death rates and air pollution are properly measured. Merging all these factors in one study can be very vital in a developing country like Bangladesh, where the covid 19 infection and the fatality rate was substantial due to higher population density. Again, the air pollution is extremely high but there is a lack in managerial activities. Here, climate change is a major concern for finding the ground-based station to detect the air pollutants and inhaling catastrophic air pollutants.

To contribute to the general objective of providing insights into the air quality before and during covid 19, this study observes and examine the spatial pattern of air pollutants. For that the specifical focus will be given on NO_2, O_3, CO, SO_2 as well as the AOD derived from MODIS during the initial heat of the COVID-19 over Bangladesh from March 2019 to October 2020. The shutdown phase in Bangladesh mostly includes the months of April through July 2020 for the very first wave, and partially August because the restrictions were progressively eased in August.

Hence, the specific goals of the study are as follows i) to measure the changes in the intensity of different air pollutants deprived from satellite images using Google Earth Engine (GEE) Platform from April–July 2019 and from April–July 2020. ii) to measure the climatic and meteorological impact such as temperature and rainfall upon air pollutant concentrations iii) to find whether there is a relationship between covid death rates and air pollutant concentration.

This study can contribute to different dimensions of policymaking. This study can help to explore different factors related to air

quality. It might pave the path for studies related to air monitoring, environmental effects of air quality. It can also encourage further air quality and climate change studies. Policymakers, urban planners, architects, environmental activists, and government officials will be influenced by this research to develop more thorough short- and long-term mitigation methods for improving air quality and lowering the burden of diseases and disabilities related to it. Setting up a ground-based surveillance system is expensive and complicated for developing nations. Compared to conventional ground-based air quality monitoring devices, it can be a more effective and affordable technique to measure air quality in developing nations. This study can be a point of reference for them.

2. Methodology

2.1. Study area

With 64 districts and a population of 167.9 million people, Bangladesh is an emerging country in southern Asia (BBS, 2015). It is located at 23.777176, 90.399452. Bangladesh's territory stretches for 820 km from north to south and covers 1,47,570 square kilometers.

(Rohr et al., 2008). The country's average elevation is around 30 feet above mean sea level, and it has a tropical monsoon climate with hot, wet summers and dry winters (Bhuiyan and Al Baky, 2014). The most populated cities in Bangladesh are Dhaka, the capital, and Chittagong, the country's economic hub. The research region, as well as its Land Surface Temperature in 2022, is depicted in Figure (1). In this study, four months from the two distinct years 2019 and 2020–April, May, June, and July—were chosen.

The strict lockdown was implemented in Bangladesh on March 25, 2020. It can be said that April 2020 was the first full month that was under full shutdown, and it lasted until the month of July 2020 (Kamruzzaman and Sakib, 2020). After July, the government decided to somewhat relax the lockdown. From August, vehicles, industries, and mills began operating once more. So, these four months were picked to compare the effect of the 'severe shutdown' on air quality in two different years 2019 and 2020. Climatic variability was a factor in the selection of these moths as well. In Bangladesh, the summer seasons are April and May, and the monsoon season begins in June. To observe the effects of seasonal changes on air quality, two distinct seasons are selected.

Bangladesh has seen tremendous air pollution because of rapid population expansion, unregulated urbanization, and industry, increased motorized car traffic, and transportation operations. Bangladesh has also been ranked as the world's eighth-largest emitter of PM2.5 (Alam, 2009). Additionally, due to the present ecological disturbance, Bangladeshis are suffering from several illnesses, including eye pain, excruciating headaches, blood circulation problems, respiratory issues, and even early death. 2019 saw 173,500 deaths in Bangladesh as a result of air contamination, up from 50,000 in 2017, and the death rate has been rising year after year as pollutant emissions have increased (Begum et al., 2013).

2.2. Data collection

As stated earlier, in this study, a comprehensive approach has been adopted to examine the effect of COVID-19 on air quality was incorporated for two different periods, following the GEE platform. The period was 'before the time of Covid-19 from June 2019 to August 2019 and during the time of Covid-19 from June 2020 to August 2020'. Due to GEE's ability to analyze Big Data, this approach's key uniqueness is in fact how easily it can be applied to the analysis of a large amount of data. Different air particles like AOD, NO_2, SO_2, and O_3 were measured during this timeline. In this study most of the data was collected from Google Earth Engine platform. Huge geo data proliferation, new developments in cloud computer science, and big data processing services are known as a
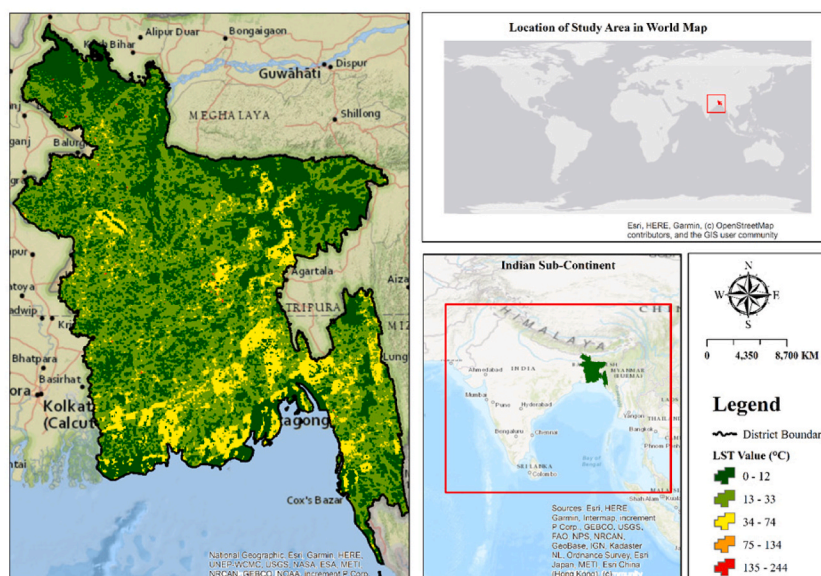

Fig. 1. Study area.

change maker of the future Remote sensing (RS) application. Without the burdens of conventional data analysis techniques in this area, GEE is effectively opening the way for scholars, experts, and designers to quickly extract meaningful information from big RS datasets (Amani et al., 2020). Users can also utilize JavaScript to implement their own algorithms with a basic understanding of the language. GEE also includes hundreds of pre-built functions that are easy for a wide range of users to understand and use. Any user is compelled to utilize this computation platform for LCLU, agricultural, hydrology, environmental calamities, and other functions due to these advantages. (Amani et al., 2020).

2.2.1. Air pollutant data

Air pollutant	Image name	Band name	Unit	Min	Max	Description	Data set provider
Nitrogen Dioxide (NO_2)	Sentinel-5P OFFL NO2: Offline Nitrogen Dioxide	NO2_column_number_density	mol/m^2	−0.00051	0.0192	Total NO_2 vertical column (ratio of the slant column density of NO_2 and the total air mass factor).	European Union/ESA/Copernicus
Aerosol Optical Depth (AOD)	MCD19A2.006: Terra & Aqua MAIAC Land Aerosol Optical Depth Daily 1 km	Optical_Depth_047		−100	5000	Blue band (0.47 μm) aerosol optical depth over land	NASA LP DAAC at the USGS EROS Center
O_3 (Ozone)	Sentinel-5P OFFL O3: Offline Ozone	O3_column_number_density	mol/m^2	0.025	0.3048	Total atmospheric column of O_3 between the surface and the top of atmosphere, calculated with the GODfit algorithm.	European Union/ESA/Copernicus
SO_2 (Sulfur Dioxide)		SO2_column_number_density	mol/m^2	−0.4051	0.2079	SO2 vertical column density at ground level calculated using the DOAS technique	European Union/ESA/Copernicus
Carbon Monoxide (CO)	Sentinel-5P NRTI CO: Near Real-Time Carbon Monoxide	CO_column_number_density	mol/m^2	−279	4.64	Vertically integrated CO column density.	European Union/ESA/Copernicus

2.2.3. Temperature and rainfall data

Temperature data of Bangladesh has been collected from MOD11A2 version 6. In a grid of 1200 × 1200 km, MOD11A2 version 6 offers an average 8-day per-pixel Land Surface Temperature and Emissivity (LST&E) with a spatial resolution of 1 km. The CHIRPS Pentad: Climate Hazards Group InfraRed Precipitation with Station Data was used to gather rainfall information. It gives mean rainfall information for any region in mm.

Nexus Between Air Pollutant Concentrations and Temperature, Rainfall, Covid-19 Deaths:

Temperature, Rainfall has a direct impact on Air Pollutant Concentrations. This research utilized Air Pollutant Concentrations and Temperature, Rainfall data using Google earth Engine.

The analyses of Pearson's correlation (Eq. (4)) and linear regression (Eqs. (1)–(3)) were carried out (Lind et al., 2012). Eq. (1) provides the basic equation for linear regression.

$$y = a + bx \tag{1}$$

Here, a and b can be projected from Eqs. (2) and (3).

$$a = \frac{\left(\sum y\right)\left(\sum x^2\right) - \left(\sum x\right)\left(\sum xy\right)}{n\left(\sum x^2\right) - \left(\sum x\right)^2} \tag{2}$$

$$b = \frac{n\left(\sum xy\right) - \left(\sum x\right)\left(\sum y\right)}{n\left(\sum x^2\right) - \left(\sum x\right)^2} \tag{3}$$

In addition, the calculation of Pearson's correlation is given in Eq. (4).

$$r = \frac{\sum(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{(x_i - \bar{x})^2(y_i - \bar{y})^2}} \tag{4}$$

where r = correlation coefficient, x_i = values of the x— variable in the sample, x = mean of values of the x—variables in the sample, y_i = values of the y—variable in the sample, y = mean of the values of the y—variables in the sample.

2.3. Data processing and methods

In this study several steps have been performed to achieve the target. 1) For data spanning the years 2019 and 2020, from where monthly NO2, SO2, O3, CO, and AOD images and their statistics were retrieved; 2) The connection between monthly averages of meteorological and climatological parameters and monthly averages of satellite-based pollutants has been evaluated; 3) The connection among air contaminants and Covid 19 death rate has been examined. There are a lot of methods can find in the literature to analyze satellite images to measure air quality concentration such as ENVI, ERDAS, Google Earth Engine and even ArcGIS. But most of the analysis and data processing in this study were done by Google Earth Engine. Because of the users frequently utilize it as a resource for ground records or quotations. It offers free, open-source image data that is accessible and supports the community of people who are interested in maps. This up-to-date, high-resolution collection of the landmass of the Earth represents a major, increasing, and mostly untapped resource for scientific research. (Ragheb and Ragab, 2015). The front-end is easy to use and offers a practical setting for the creation of interactive data and algorithms. Users can also add data and collections and curate them, with Google's cloud resources handling all the processing (Adam et al., 2010). Many experiments such as land cover (Li et al., 2007), air quality (Rana et al., 2022), crop health analysis (Singh et al., 2021), and environmental means controlling (Lin et al., 2018) can be performed in this platform. Different programming language can be used in the Google Earth Engine platform. Google Earth Engine enables its users to insert satellite image links and country boundary links to the code editor. The programming language used in the code editor for this research was Java Script API. One of the foundational technologies of the World Wide Web, alongside with HTML and CSS, is the programming language known as JavaScript, or JS. Filter array was used following the application of both SI connections and country table links. A picture can be filtered using the JavaScript filter array function according to predetermined criteria. The JavaScript filter method loops through the array's current values and returns those that pass. Code editors consist of three different features such as Scripts, Docs and Assests. Assests enable its users to import shape files, excel sheets and other document. The vector data of Bangladesh was imported which was downloaded from DIVA GIS. The whole coding was done in the scripts feature. An encoded URL can be used to share Code Editor scripts. For generating a script URL, a variable function 'var' has been used. After importing the shapefile into the assets, the code writing in the scripts was undertook (Amani et al., 2020). At first, see.Image Collection was used to import the satellite image in the variable. Filtering of the satellite image was done by country boundary shape file which was imported in the Assests. Selecting the band for measuring the concentration of the gas was important. The select () function has been used for this. The element on the page with the specified id, class, or tag name was searched for using the select () function. In most of the cases 'column number density' band has been selected, and it was again filtered by date. After that print function was used then it was noticeable that the output number was very large, so a function called reducer. Mean () was used. In Earth Engine, reducers are a method for combining data across time, space, bands, arrays, and other data structures. As a result, a collection of images was reduced using the median reducer, where the composite value is the median across all bands throughout time. Then a parameter for band visualization that used a distinct color for each value was introduced.

Different palette such as 'black', 'blue', 'purple', 'cyan', 'green', 'yellow', 'red' have been used for different types of gas. Band visualization maximum and minimum value was different for each gas. For example, the maximum and minimum visualization value for O_3 gas were 0.12 and 0.15 and for AOD gas were 0 and 100. After that, the clip () function has been used to clip the study area from the image collection. Study area has been clipped from the average gas value. An array function has been used to store image, file format, region, and scale when exporting the image to drive. File format of each gas was 'GeoTIFF ' and the scale was 30. For making time series chart an array function consisting of image collection, reducer, region, and scale was used. For printing the charts, ui.Chart.
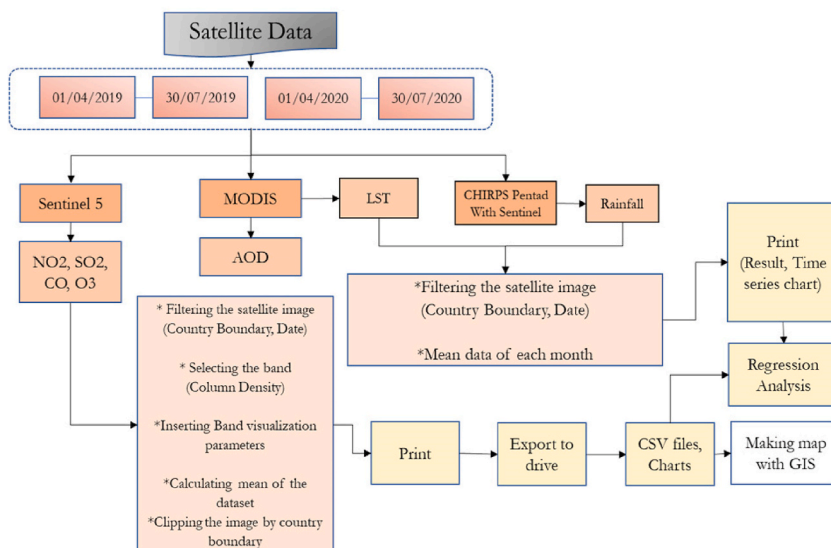

Fig. 2. Methodological flowchart.

image.series function was used. In most of the cases, variable filter date function was used to measure the concertation of gases with time. Finally printing the chart showed the time series in the console. For making the map from the output, ArcGIS has been used. Different climatic parameters such as LST and Rainfall mean data have been acquired from the GEE Platform in CSV tabular format. A relationship between the climatic parameters and gas particles has been shown in this study using Pearson correlation (see Fig. 2).

3. Result and analysis

3.1. Distribution of NO2 column density over time and space over Bangladesh

On March 24, 2020, Bangladesh imposed a lockdown and prohibited all passenger travel on domestic sea, rail, and air networks (Kamruzzaman and Sakib, 2020).

It resulted in a decrease in energy use and oil demand. Additionally, it offered a wonderful chance to compare some pollutant concentrations to evaluate its effects on air quality. Although a number of important factors may affect the amount of air pollution, this study's methodology was based on the utilization of those factors and the studies that followed (Ghasempour et al., 2021). One of the gasses that exist in the atmosphere is NO_2. After imposing the lockdown, the concentration of NO_2 gas significantly dropped throughout the country.

Major differences can be seen in Dhaka and Chattogram (Figs. 3 and 4). Most of the industries are situated in these two major cities. Due to the imposing of the lockdown, the concentration dropped down in those regions. Next three months of 2020, the concentration value slightly increased all over Bangladesh, but it was lower than in 2019. Similar results can be seen in other studies (Rana et al., 2022). From the (Figs. 3 and 4)., it is visible that the concentration value was lower in April 2020 compared to April 2019. In May 2019, the concentration value was slightly lower than in May 2020. But in the next two months concentration value decreased a lot in post-Covid timeline compared to pre covid timeline.

3.2. Distribution of aerosol optical depth in space and time (AOD) over Bangladesh

Aerosols, which are typically dust particles like ash, mist, or fog, are suspensions of solid elements or fluid drops in a gas. Large human habitats are frequently found close to human-made aerosols. The optical depth of the atmosphere is the telemetry parameter utilized in this context. The ratio of solar waves propagated and absorbed in the atmosphere along the wavelength and the distance traveled is used to determine the aerosol optical depth (AOD) index, which is a measurement of an aerosol (Ghasempour et al., 2021).

This index, which is often calculated along a vertical path, is a mathematical statistic to show the density and concentration of particles in the atmosphere (Filonchyk et al., 2019). When creating monthly AOD images, masking operation was used on the AOD Quality Assessment (AOD QA) band to offer the highest quality AOD data (Figs. 5-7) Regarding the AOD's geographic distribution, April, May, and June 2020 have lower AOD concentration values compare to 2019 (Fig. 5 and Fig. 7). But the concentration of AOD was lower in July 2019 compared to 2020. A considerable reduction in the monthly AOD distribution was seen in April, the lockdown month after, in 2020 compared to the same month in 2019, demonstrating the lockdown's significant impact on AOD reduction.

Since, April 2020 was the most restricted month for lockdown in the country AOD concentration reduced to a higher level although the AOD concentration differed throughout the region. From April to May the spatial distribution was 768.45 km–961.63 km in 2020 which was lower than the AOD distribution in 2019 which were 839 km and 1082.21 km. From June 2020 restriction was relaxed throughout the region and the density was lower than found in the previous month.
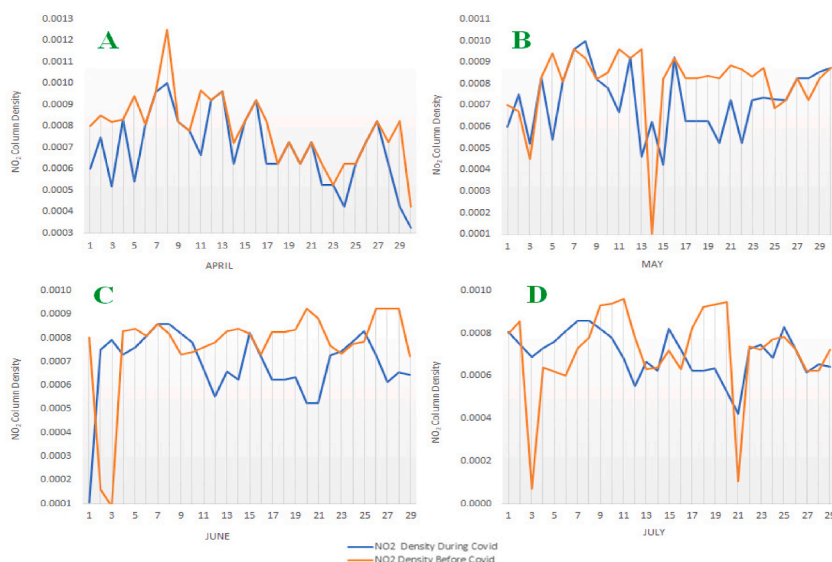

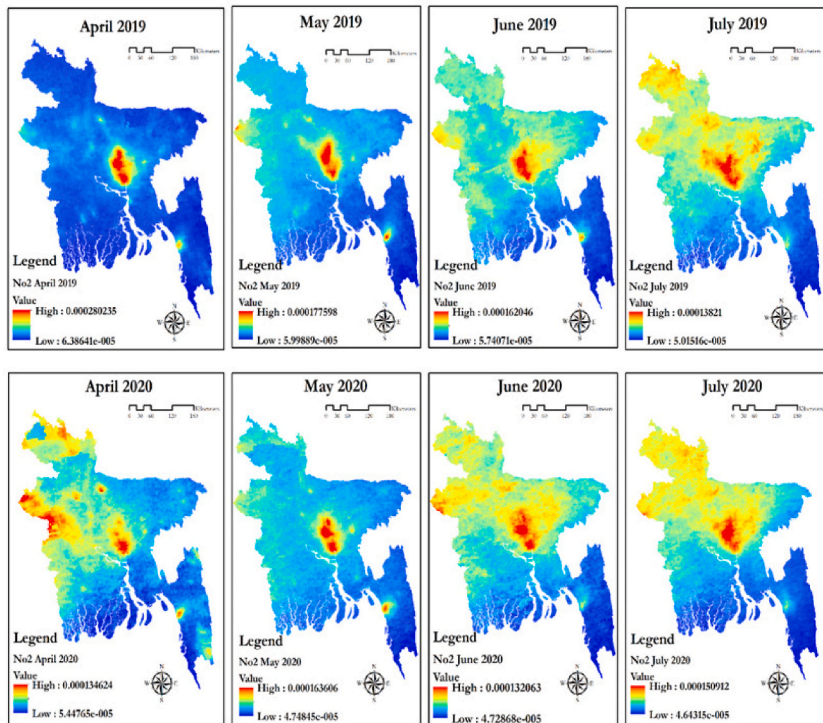**Fig. 3.** NO_2 density per day (A) April, (B) May, (C) June, and (D) July 2019 vs 2020.

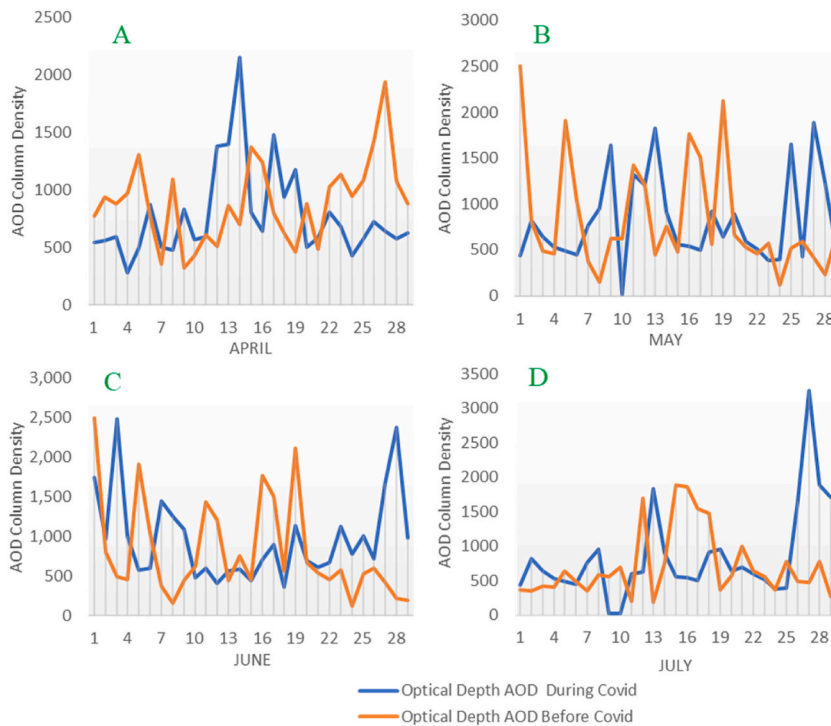**Fig. 4.** NO$_2$ Gas Depth Map of Bangladesh from April to July (2019 vs 2020).

Fig. 5. AOD density per day (A) April, (B) May, (C) June, and (D) July 2019 vs 2020.
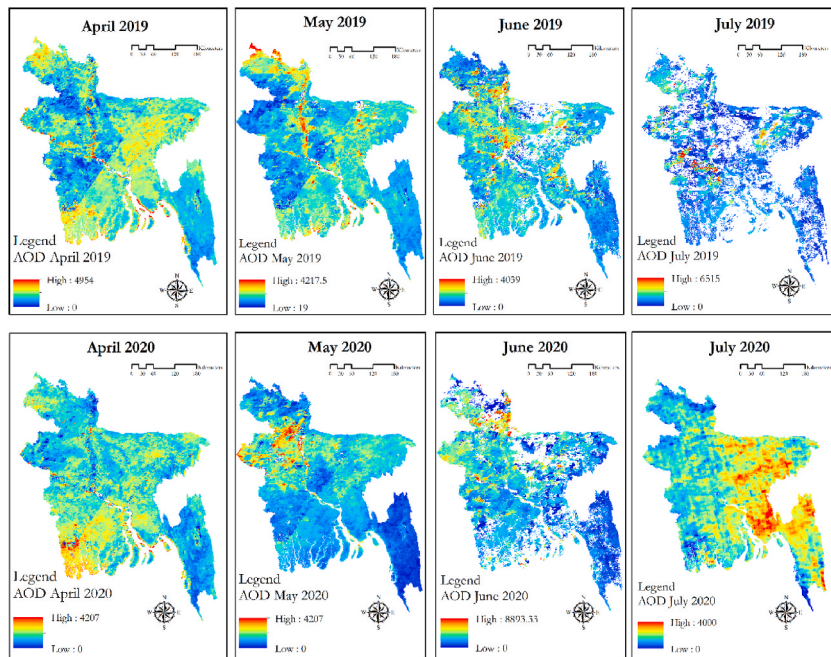
Fig. 6. Aerosol Optical Depth Map of Bangladesh from April to July (2019 vs 2020).

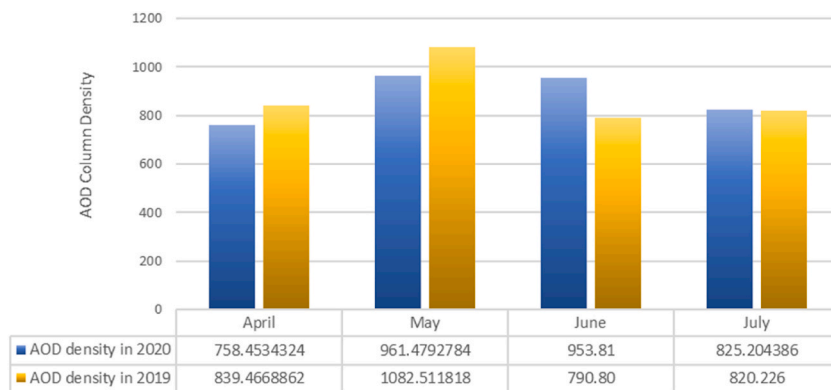|	April	May	June	July
■ AOD density in 2020	758.4534324	961.4792784	953.81	825.204386
■ AOD density in 2019	839.4668862	1082.511818	790.80	820.226

Fig. 7. AOD density at April–July in the year 2019 vs 2020.

3.3. Distribution of O₃ column density in space and time over Bangladesh

The (Figs. 8-10) represents the daily O_3 data from April to July (see Fig. 7). From the figures, it can be said that O_3 density was higher in April 2020 compared to April 2019. O_3 concentration in April 2020 was 0.131 mol/m2 and in April 2019 it was 0.1246 mol/m2 (Fig. 8 and Fig. 10).

It dropped a bit in the next month but the overall density of O_3 was higher in 2020(0.127 mol/m2) compared to 2019 (0.123 mol/m2). The Lockdown effect was observed in June and July. O_3 density of 2020 (0.123 mol/m2), for the first time, was lower than 2019 (0.125 mol/m2) in June. Finally, in July O_3 density value of 2020 was again lower than 2019.

From the O_3 gas depth map (Fig. 9), it is observed that O_3 concentration was heterogenous throughout the country. The concentration value was higher in the Rangpur district, and it was comparatively lower in the Chattogram district. The impact of lockdown has been seen in July. From Fig. 10, it is visible that in July the O_3 value dropped a lot in post-covid time compared to pre-covid time.

3.4. Distribution of CO column density in space and time over Bangladesh

One of the main sources of CO in the environment is vehicle exhaust. Since no vehicles were being used during the lockdown, a decrease in CO emissions was anticipated. But from the (Figs. 11 and 12) it is observed that the concentration of CO did not improve too much due to the Covid 19 lockdown.

As a result, the improvement in air quality in terms of CO was not sustained, much like the prior findings (Ahmed et al., 2022). In
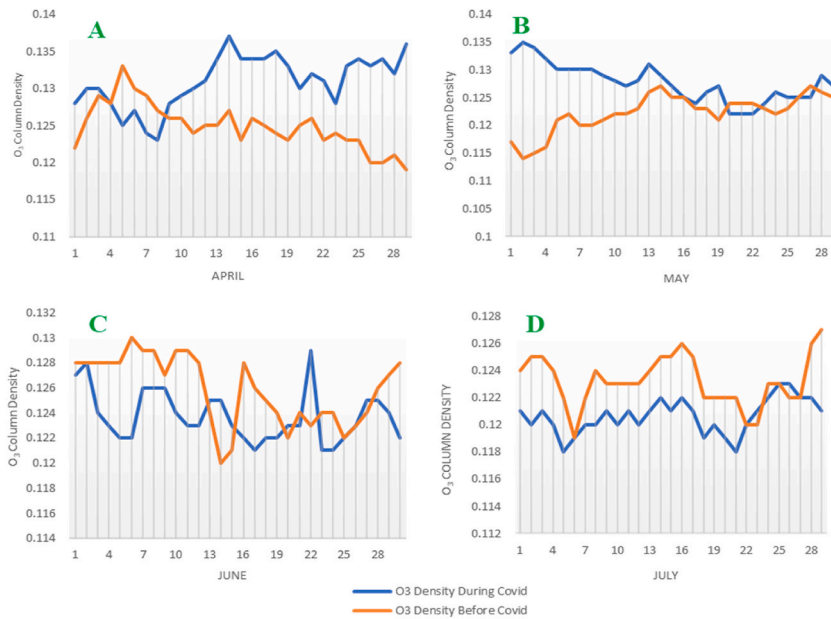
Fig. 8. O_3 density per day at (A) April, (B) May, (C) June, and (D) July 2019 vs 2020.
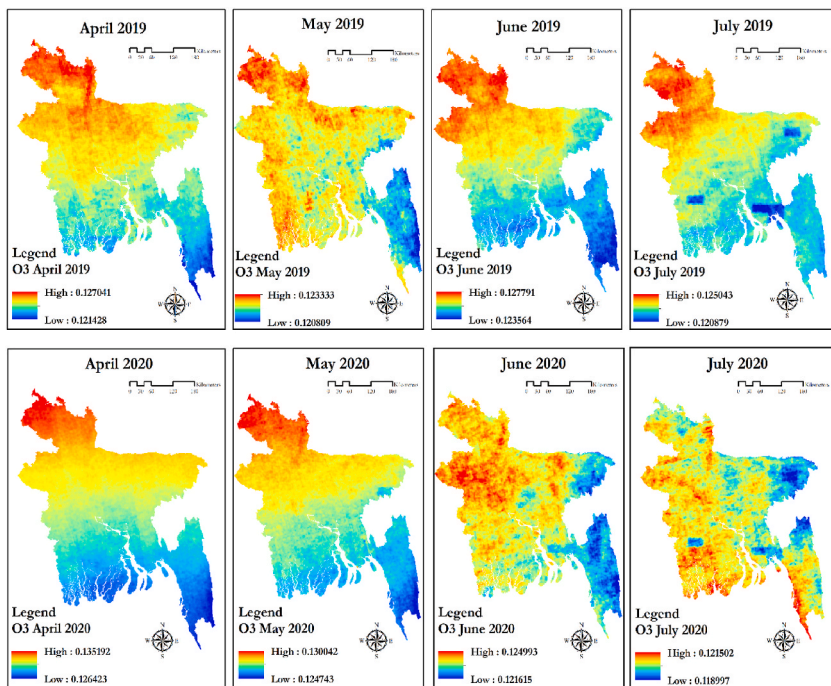

Fig. 9. O_3 Depth Map of Bangladesh from April to July (2019 vs 2020).

April and June, the difference between the pre and post covid timeline was not seen.

Gradually the condition of CO density improved in 2020 due to lockdown but the difference is not too much. CO density in June 2020 was 0.03692 mol/m2 and it was 0.04268 mol/m2 in 2019 (Figs. 11 and 12).

3.5. Distribution of SO_2 column density in space and time over Bangladesh

One of the trace gases in the troposphere, SO2, is mostly created by industrial processes and volcanoes. Oil and coal contain sulfur compounds, which when burned result in the generation of SO_2 (Ghasempour et al., 2021). The monthly average SO_2 column density's spatiotemporal fluctuations over Bangladesh were examined as in (Figs. 13-15).
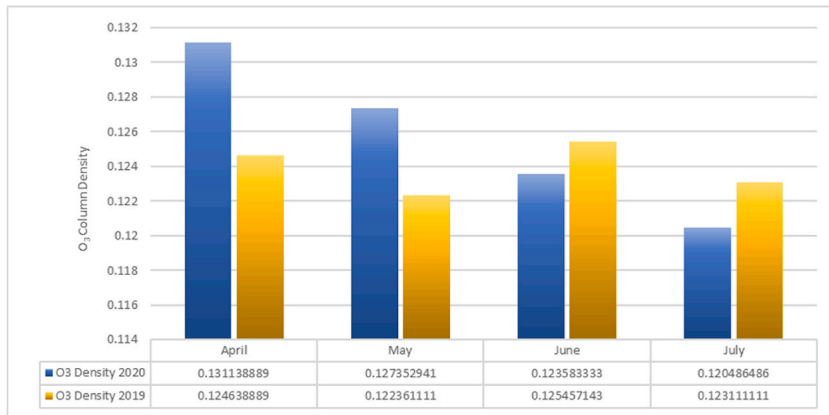
Fig. 10. O$_3$ density per month from April–July in the year 2019 vs 2020.
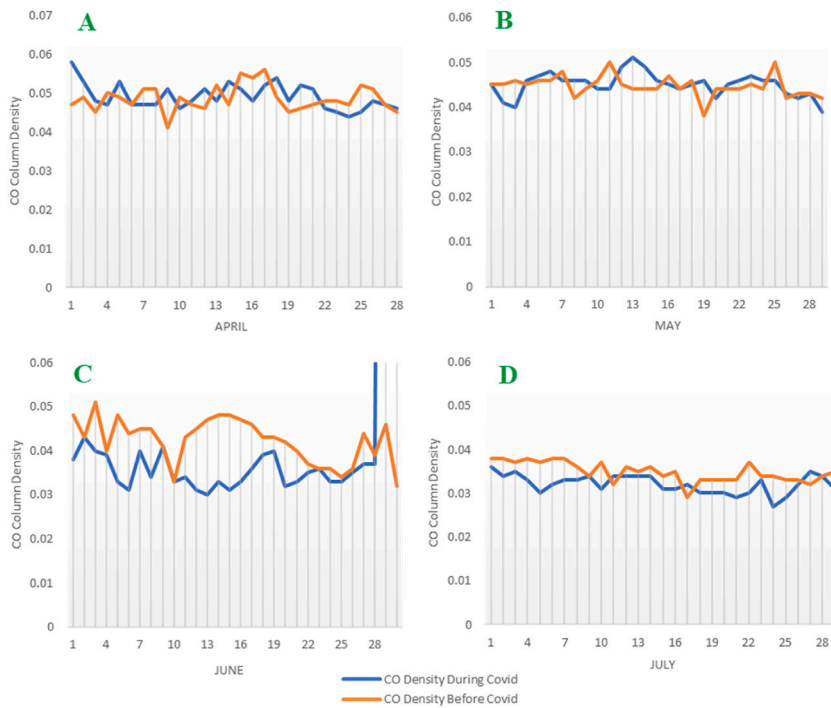

Fig. 11. CO density per day at (A) April, (B) May, (C) June, and (D) July 2019 vs 2020.

From the (Fig. 13 and Fig. 15) it can be said that in April 2019, the SO$_2$ value was higher than in April 2020. But it gradually decreased in the upcoming month. In May, the post covid SO$_2$ density value was lower than the pre covid SO$_2$ density value. SO$_2$ density value was lowest in June for both pre- and post-covid timeline. In July the density value increased in both timelines, but they were almost the same.

The monthly average SO$_2$ measurements during the lockdown period were somewhat higher in 2020 than they were during the same time in 2019. Numerous sorts of worldwide study have noted the decrease in SO$_2$ during lockdown (Collivignarelli et al., 2020). When we examine the SO2 map, we can see that the SO$_2$ value is higher in the Khulna region compared to others in 2019 which decreased in the post-lockdown period.

It is a matter of concern that SO$_2$ was not higher in Dhaka in 2019 but it increased a lot post lockdown time though most of the industries are situated in this region.

3.6. Nexus between air contaminant concentrations and temperature in Bangladesh

Weather conditions such as precipitation and temperature have a substantial impact on the dynamics of airborne pollutants (Oji and Adamu, 2020). Fig. 16 (I) depicts the distribution of air pollutant concentrations in Bangladesh during the study, as well as the
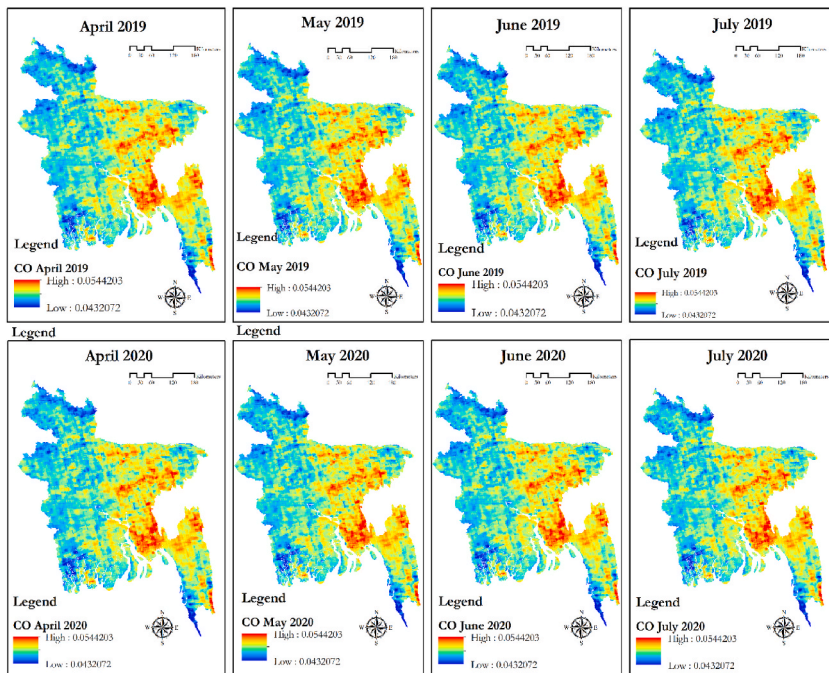
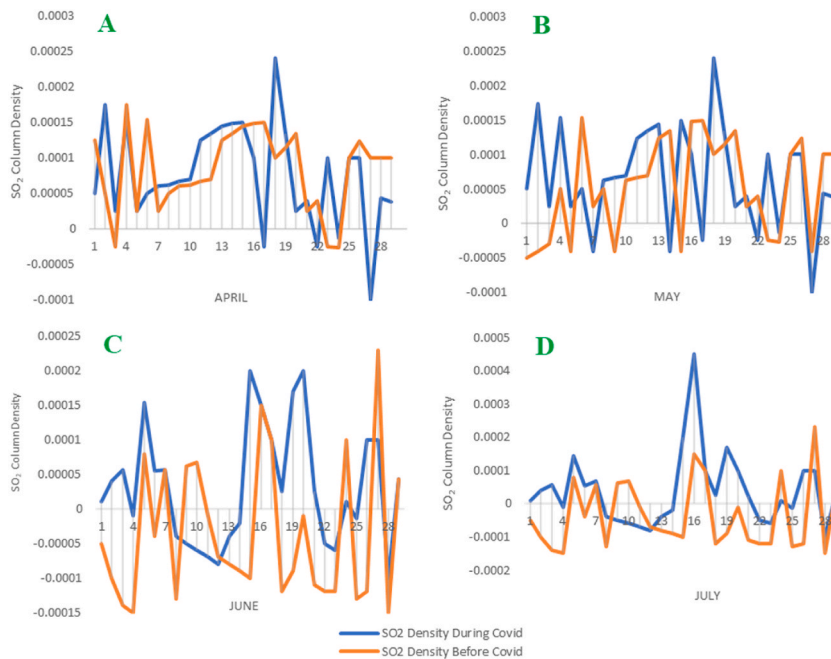**Fig. 12.** CO Depth Map of Bangladesh from April to July (2019 vs 2020).

Fig. 13. SO_2 density per day at (A) April, (B) May, (C) June, and (D) July 2019 vs 2020.

correlation coefficient and Pearson's coefficients of air pollutant concentrations related to temperature. During the study, the average daily temperature fluctuated between 16- and 32-degrees Celsius Fig. 16 (I). With an R_2 value of roughly 0.435 and Pearson's r = - 0.662, this research reveals an inverse association between NO_2 column density and temperature. A similar result has been found for SO_2 with an R^2 value of 0.462 and Pearson's r = - 0.684. The result shows strong negative correlation which was also found by (Faisal et al., 2022). But in the case of CO, it showed a positive correlation with R^2 = 0.580 and Pearson's r = - 0.764 which indicates the density of CO increased with the increment of temperature. The density of O_3 increases with temperature having R^2 = 0.506 and Pearson's r = 0.714 and finally AOD also shows a positive correlation with temperature and its R^2 = 0.431 and Pearson's r = -0.659.
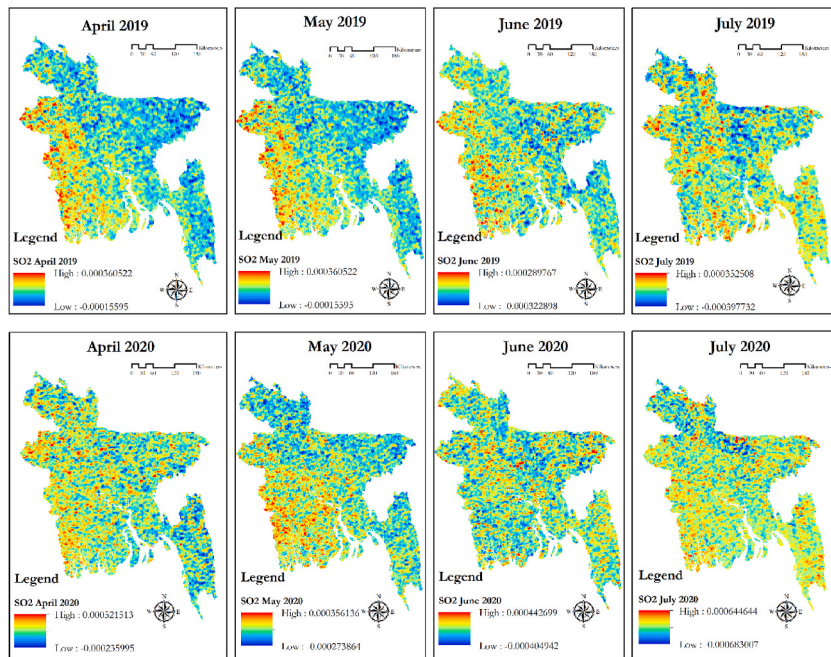
Fig. 14. SO_2 density per day at (A) April, (B) May, (C) June, and (D) July 2019 vs 2020.
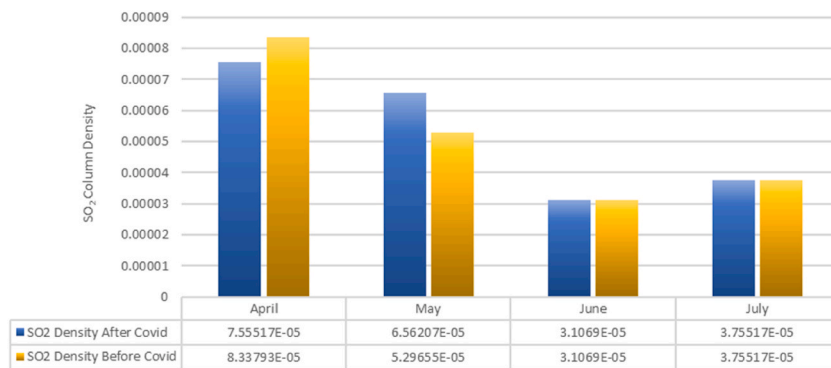

Fig. 15. SO_2 density per month from April–July in the year 2019 vs 2020.

The connection demonstrates a significant relationship among temperature and different types of air pollutants and their density increases/decreases with the rise of temperature leading that temperature can vitally factor for air quality in the country.

3.7. Nexus Between Air Pollutant Concentrations and rainfall in Bangladesh

This study evaluated the relationship involving air pollutants and rainfall and showed it in Fig. 16 (II) to assess the effects of rainfall on air pollutants concentrations in the air. Pearson's correlational analysis was also used to examine the data. With a significant R^2 value of 0.487 and a Pearson's correlation value of 0.705, Fig. 16 (II) depicts the adverse connection between No2 column density and rainfall. With an R^2 value of roughly 0.151 and Pearson's r = - 0.396, this research reveals an inverse association between CO column density and rainfall. O_3 column density and rainfall also show a negative correlation with an R^2 value of 0.304 and Pearson's r = - 0.556. AOD and SO_2 column density were also found to be negatively correlated with rainfall with an R^2 value of O.383 and O.057 respectively. This means that if the amount of water increased in the atmosphere pollution densities could be lower down. Rain functions as an environmental cleanser, decreasing pollution levels in the atmosphere by minimizing pollutant levels in the air owing to disintegration and dispersion dilution caused by rain. For various research regions, the majority of a recent study suggested an reverse correlation between rainfall and air pollutants (Chen et al., 2016; Oji and Adamu, 2020).

3.8. Air pollutants and COVID-19 deaths: a relationship

In previous decades, people inhaled these deadly chemicals and died as a result. As a result, identifying the relationship among COVID-19 mortality and air contamination is a critical endeavor. Our regression analysis findings showed satisfactory positive
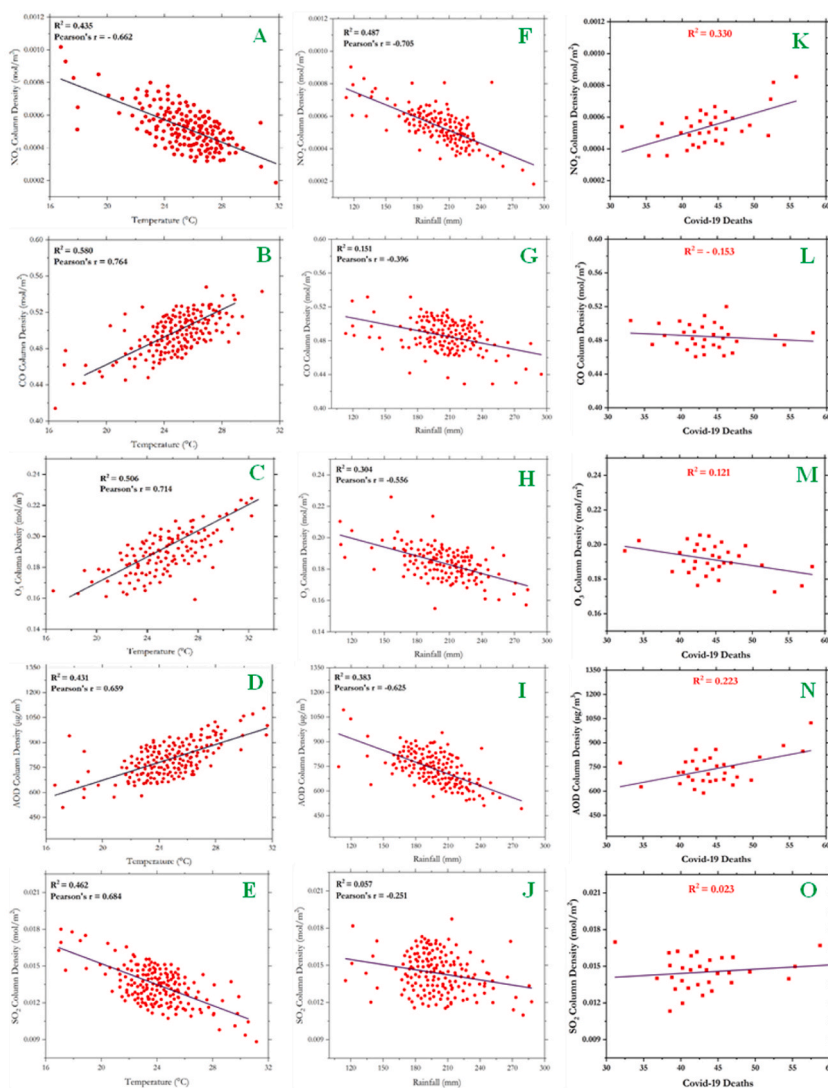
Fig. 16. (I) Nexus between air pollutant concentrations ((A. - No$_2$ (B) – CO (C)– O$_3$ (D)- AOD (E)- SO$_2$) and Temperature in Bangladesh, (II) Nexus Between Air Pollutant Concentrations ((F. - No$_2$ (G) - CO (H)– O$_3$ (I)- AOD (J)- SO$_2$) and Rainfall in Bangladesh, (III) Association Between Air ((K). - No$_2$, (L). - CO, (M)- O$_3$, (N)-AOD, (O)– SO$_2$) and COVID-19 Deaths.

associations with NO$_2$, AOD, and SO$_3$ column density in this respect. NO$_2$ ($R^2 = 0.330$; r = 0.37, p = 0.028), AOD ($R^2 = 0.223$; r = 0.497, p = 0.032), and SO$_3$ ($R^2 = 0.023$; r = 0.162, p = 0.041) air pollutants were shown to have significant relationships with COVID-19 fatalities (Fig. 16 (III)). With O$_3$ and CO airborne pollutants, there were poor/negative relationships between these parameters. Due to the strong correlation between these air contaminants and COVID 19, deaths it can be said that because of the long-term absorption of harmful pollutants, persons living in areas with low air quality are more sensitive to COVID-19. Several researchers attempted to find the linkage among different pollutants and covid 19 deaths and the majority of them discovered a link between these contaminants and Covid 19 fatalities. Long term inhalation of low-quality air certainly weakens the immunity system and that might help to increase the rate of virus replication and eventually cause death (Cole et al., 2020; Feng et al., 2019; Wu et al., 2020).

4. Discussion

So many analyses have been performed to measure the impact of the Covid 19 pandemic on the Environment. Detailed reviews have been done to address the Covid 19 and its environmental influences (Praveena and Aris, 2021; Ahmed et al., 2022). Additionally, some studies have examined how the COVID-19 will affect the Sustainable Development Goals (Shulla et al., 2021). All this research showed that the environmental effects of the steps adopted to stop the deadly virus's spread were both good and bad. Regarding the positive effects, most factories were shut down, automobile circulation was restricted, greenhouse gas emissions were reduced, water pollution was reduced, and environmental noise levels were at historic lows. Negative impacts were an increase in medical waste and household plastics/waste, and careless and overusing of masks, gloves, and disinfectants (Ghasempour et al., 2021). In this research,

the spatial-temporal patterns of air pollutants resultant from Sentinel-5P TROPOMI, specifically O2, O3, CO, and SO2, and MODIS-derived AOD are tracked and examined between April and July 2019 and April and July 2020, including the first upsurge period of the COVID-19 epidemic over Bangladesh.

Data analysis and the retrieval and processing of satellite imagery have both been done using the GEE platform. April and May are the summer season in Bangladesh and the Rainy season starts in June. So, the timeline of our observation consists of two seasons - summer and rainy season. According to our obtained results, the NO_2 concentration value was lower in post covid timeline compared to pre covid timeline in the summer. Due to excessive rainfall in the rainy season NO_2 value dropped on both sides but the NO_2 value in post covid timeline was lower. The same kind of results are seen in other studies (Rana et al., 2022). AOD concentration improved a lot compared to the post lockdown scenario at the start of the lockdown. During the strict shutdown in 2020 (March to May), Bangladesh's largest cities saw noticeably lower amounts of dust-type particles than they had in 2019 (Qiu et al., 2021). But the concentration slightly increased in May. This rise in smoke-type aerosols may be owing to improperly implemented stringent lockdown that allowed some sporadic running of brick kilns, open burning of solid waste, and agricultural waste (Qiu et al., 2021). O3 concentration was high compared to pre-lockdown timeline at the start of the lockdown but it eventually improved in June and July. But the overall concentration was higher compared to pre-corona timeline (Fig. 12). O3 rose by 8%–12% across the nation (Qiu et al., 2021). The reported increase in ozone during the lockdown and a minor drop during the partial lockdown are likely to be the result of several forces working together. According to Nichol et al. (2020), a few reasons may be contributing to the increased creation of secondary pollutants (especially ozone). The creation of secondary pollutants (nitrates, sulfates, and organic compounds) may be enabled by an increase in the atmosphere's ability to oxidize due to a decrease in NOx, for instance, or it may be caused by the VOC/NOX ratio (Sillman et al., 1990). CO concentration during lockdown was slightly lower than the pre covid timeline. Given that incomplete fuel combustion, which results in incomplete oxidation of hydrocarbons, is the primary cause of high CO emission, primarily from automobiles (Aydin, 2013), a considerable reduction in CO due to restricted vehicle movement seems reasonable (Islam et al., 2021a). SO_2 Value was slightly higher in April compared to pre covid timeline but it eventually decreased due to the lockdown effect. However, due to the concentration of industrial zones in these cities, a sizable decline was also noted in Dhaka, Narayanganj, Khulna, Rajshahi, and Gazipur, ranging from 40.5% to 66.6% (Islam et al., 2021b). The largest decrease in SO2 concentrations is therefore reasonable given the cessation of all industrial activity and the restriction of vehicle movement. The reduction in SO2 concentrations during the partial or entire lockdown period compared to the pre-lockdown period was reported in New Delhi (India) and Milan (Italy), where similar results were seen (Islam and Chowdhury, 2021). Previous studies showed how climatic and meteorological impacts influence air quality concentration (Faisal et al., 2022). Due to the country's geographical location, which causes different seasonal variations, we believe meteorological factors have a significant impact on air quality throughout the period before and after the lockdown (Islam et al., 2021a). This study verifies through statistical analysis that high temperature and rainfall clears the atmosphere by decreasing the concentration of air pollutant and there is a strong relationship between climatic and meteorological impact and air pollutants. Finally, an association between air pollutants and COVID-19 deaths is shown in this study. It is verified that long-term inhalation of air pollutants has worked as a push factor to increase covid cases and deaths.

Through the experimental results a comprehensive scenario of the air pollutants between different timelines can be clearly seen. Experimental results will help to better understand that restrictions upon vehicles and man-made pollution can be a useful method to improve the overall air quality. Due to its geographic position, which has different seasonal fluctuations, it has been proved that meteorological factors have a significant impact on air quality during the pre-lockdown and during a lockdown which is shown in the experimental results. The main barrier of this study was that no ground-based verification has done here. As, satellite must scan the entire column of air underneath it to measure air pollution, it is sometimes challenging to determine the amount of pollution in the lowest few meters where we breath. So, this study revealed the integration of GEE, RS and ArcGIS to minimize the shortcomings.

5. Conclusion

This study is an approach to detect pre and post covid air pollutant concentration. In this study, we have used satellite-based imagery to detect the changes of air pollutants over pre and post covid timelines. For a developing country like Bangladesh where ground station-based air pollutant measurement is not available throughout the region and is costly, satellite imagery can be an effective way to measure the changes. Findings show that the condition of most of the air pollutants has improved due to the lockdown. Implementation of strict lockdown shut down of industries and restrictions upon vehicles have worked as an important factor to decrease the concentration of air pollutants. In Bangladesh, climatic and metrological impacts have a high influence on air quality. For this reason, air pollutant concentration differs between different seasons. Inhalation of dangerous air pollutants for a long time is found to be a push factor to increase the death rates as cities with high air pollution (Dhaka and Chittagong) have high death rates. A strong relation between air pollutant concentration and the death rate is also found. Urban planners, policymakers, and change agents are increasingly actively discussing the connection between airborne pollution and urban health challenges (Faisal et al., 2022). Future studies can be done to detect how this improvement can sustain. The major limitations of this study are that we could not verify most of the results by comparing them with ground-based station data. Limitations of the study are tried to be mitigated by verifying the results with previously published papers. This research will influence the policymakers, urban planners, architects, environment activists, and government officials to better understand the sources of atmospheric emissions to plan substantial proof short- and long-term mitigation strategies for improving air quality and reducing the associated disease and disability burden.

Author's contribution

Md. Nazmul Haque: Conceptualization, Writing – original draft, Editing, Investigation, Review; **Md. Shahriar Sharif, Rhyme**

Rubayet Rudra, Mahdi Mansur Mahi: Writing – original draft, Software, editing, Review; **Md. Jahir Uddin**: Reviewing the draft, editing, Review; and **Radwan G. Abd Ellah**: Reviewing the draft, editing, Review.

Ethical statement

1) <u>Compliance with Ethical Standards:</u> In line with national ethical standard of research of Government, my university has developed one. Our research fully adheres to that ethical guideline.
2) Funding (optional): This research does not receive any external funding.
3) Conflict of Interest: The authors hereby declare that there is no conflict of interest
4) <u>Ethical Approval:</u> Our research has ethical clearance-the research protocol is approved. As our research does not involve any manipulation of human or animals, and there is not risk involved in this research, therefore university's local committee's endorsement was enough.
5) <u>Informed Consent:</u> All participants of our research are fully aware of our approved research protocol. We obtained informed consent (voluntary) of all persons participated in our research.

Declaration of competing interest

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

Data availability

Data will be made available on request.

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