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Analysis of the effect of COVID-19 lockdown on air pollutants using multi-source pollution data and meteorological variables for the state of Uttar Pradesh, India

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सार — इस अध्ययन में भारत के सबसे अधिक आबादी वाले राज्य, उत्तर प्रदेश में COVID-19 की असाधारण स्थिति को ध्यान में रखते हुए 2019 और 2021 के बीच की अवधि के दौरान वायु गुणवत्ता में भिन्नता का अनुमान लगाया गया है। भारत सरकार ने 25 मार्च 2020 को चार चरणों का पूर्ण लॉकडाउन लगाया, जो 31 मई 2020 तक चला। यह अध्ययन ग्राउंड स्टेशन-आधारित प्रदूषण डेटा के साथ-साथ उपग्रह से प्राप्त डेटा की मदद से इन चरणों के दौरान के प्रदूषण डेटा के बारे में जानकारी देता है। चूंकि ग्राउंड डेटा सीमित स्टेशनों पर उपलब्ध है, इसलिए 2020 की समयावधि के दौरान पूरे राज्य के लिए चरण-वार प्रदूषण मानचित्र तैयार करने के लिए एक व्युत्क्रम दूरी भारित (IDW) इंटरपोलेशन तकनीक का उपयोग किया गया है। तैयार किए गए प्रदूषण मानचित्र में PM_{2.5}, PM₁₀, NO₂, NO_x और NO₂ के प्रदूषण स्तर में तेजी से कमी और चरण-I (P1) में SO₂ और ओजोन के स्तर में वृद्धि होना लॉकडाउन की प्रभावशीलता को उचित ठहराती है। इसके अलावा, स्टेशन-वार विश्लेषण के लिए, औसत प्रदूषण स्तर के साथ-साथ प्रदूषण स्तर में बदलाव की गणना करने के लिए वर्ष 2019, 2020 और 2021 के लिए छह-चरण की समय रेखा तैयार की गई है। 2019 और 2021 की तुलना में, वर्ष 2020 में P1-P4 के माध्यम से औसत और मानक विचलन सबसे कम हैं, जो लॉकडाउन के कारण 2020 में प्रदूषण स्तर के सबसे कम प्रसार को दर्शाता है। इस विश्लेषण में सेंटिनल-5पी ट्रोपोमी उपग्रह डेटा भी शामिल है, जो NO₂ के लिए सट्टा प्रेक्षण देता है। सहसंबंध के संबंध में, ग्राउंड स्टेशनों और उपग्रहों से प्राप्त डेटा NO₂ के लिए सबसे अधिक और SO₂ के लिए सबसे कम सहसंबंध होता है। इसके अलावा, प्रदूषण डेटा (आश्रित) और मौसम संबंधी डेटा (स्वतंत्र) के बीच अनुभवजन्य संबंध उत्पन्न होते हैं, जिससे पता चलता है कि मौसम संबंधी डेटा के साथ बाइनरी लॉकडाउन चर का उपयोग करके प्रदूषण स्तर की परिवर्तनशीलता को व्यक्त करने की क्षमता में और वृद्धि हुई है।

ABSTRACT. The present study, conducted in the most populous state of India, *i.e.*, Uttar Pradesh, estimates the variation of air quality for the period between 2019 and 2021, taking into account the extraordinary situation of COVID-19. The Government of India imposed the four-phased complete lockdown on 25th March, 2020, which lasted until 31st May, 2020. The study deals with pollution data during these phases with the help of ground station-based pollution data as well as available satellite data. Since ground data is available at limited stations, an Inverse Distance Weighted (IDW) interpolation technique is used for the generation of phase-wise pollution maps for the whole state during the timeline of 2020. The generated maps show a sharp decline in pollution levels for PM_{2.5}, PM₁₀, NO₂, NO_x and NO, and an increase in the level of SO₂ and Ozone in Phase-I (P1), justifying the effectiveness of the lockdown. Further, for station-wise analysis, a six-phase timeline for the years 2019, 2020 and 2021 has been devised to calculate mean pollution levels as well as pollution level changes. In comparison to 2019 and 2021, the mean and standard deviation in the year 2020 through P1-P4 is the least, emphasising the least spread of pollution level in 2020 due to the lockdown. The analysis is also accompanied by Sentinel-5P TROPOMI satellite data, giving similar observations for NO₂. Regarding correlation, data from ground stations and satellites correlate most for NO₂ and least for SO₂. In addition, empirical relations between pollution data (dependent) and meteorological data (independent) are generated, which reveal that the power to explain the pollution level variability has further increased by using binary lockdown variables along with meteorological data.

Key words – Ambient air pollution, Lockdown, NO₂, Ozone, Particulate matter, SO₂.

1. Introduction

According to an estimate by World Health Organization (WHO), in the year 2012, air pollution was

responsible for nearly seven million deaths, which is double the number of death estimated until that period; the death count due to air pollution represents more than 12% of all-cause deaths; The population living in low and

middle-income countries are suffering the most with exposure to air pollution with a total of 3.3 million deaths related to indoor air pollution and 2.6 million deaths related to outdoor air pollution (WHO, 2014). Another study by WHO reports that in 2016 outdoor air pollution in both urban and rural areas caused 4.2 million premature deaths worldwide; 91% of this burden of deaths is wielded upon low and middle-income countries; this mortality is due to exposure to (PM_{2.5}), which cause cardiovascular and respiratory disease, and cancers (WHO, 2021).

Air pollution is defined as the change in natural characteristics of air caused by biological, chemical or physical contamination (Vallero, 2014). Various effects of air pollution are widely studied by researchers (Bishop *et al.*, 2018; Stern, 1977; Yin *et al.*, 2020), and a short-term as well as long-term exposure study claims that increased mortality in case of respiratory diseases is directly linked with increased airborne particulate matter (PM) and Ozone (Brunekreef & Holgate, 2002; Seaton *et al.*, 1995). The criteria for ambient air pollution guidelines are drafted using six principal pollutants, including carbon monoxide, lead, nitrogen oxides, ground-level Ozone, particle pollution (often referred to as particulate matter) and sulphur oxides. Nitrogen oxides include pollutants like NO, NO₂ and NO_x, particle pollution includes PM_{2.5} and PM₁₀ and sulphur oxides include SO₂ etc. These pollutants are generally considered for the analysis of pollution levels (CDC, 2021).

In developing countries like India and China, to make the mortality rate due to PM_{2.5} constant, the PM_{2.5} level would need to decline by 20-30% over the next 15 years merely to offset the increase in PM_{2.5} attributed mortality (Apte *et al.*, 2015; Xie *et al.*, 2016). As per the research of (Bruce *et al.*, 2006), nearly 2.6 billion of the entire population still relies on solid fuels for cooking, which contributes greatly to indoor pollution. As a result, life-threatening diseases like chronic obstructive pulmonary disease (Kurmi *et al.*, 2010), pneumonia (Naz & Ghimire, 2020), lung cancer (Sloan *et al.*, 2012), stroke, ischaemic heart disease (Bassig *et al.*, 2020) and other such diseases have flourished. Health and socioeconomic position are correlated with each other, and the working class is at a higher risk of getting caught with the disease by ambient pollution (O'Neill *et al.*, 2003). Motor traffic emission is a major concern causing air pollution in developing nations' cities (Amegah & Agyei-Mensah, 2017; Mayer, 1999). Motor use, as well as air pollution, can be controlled (Cooper & Alley, 2010; De Nevers, 2010) substantially by way of public transport, such as regional railway expansion (Lalive *et al.*, 2018) and by putting the onus on the polluters, for which proposal of a new clean air act can be a proactive step (Holgate, 2017).

Another study found that air pollution directly affects the immune system by enhancing THE lymphocyte type 2 and type 17 responses and is responsible for respiratory exacerbation (Glencross *et al.*, 2020). According to the article published in The Hindu (Correspondent, 2020), India faced the highest per capita pollution of 83.2 µg m⁻³ followed by Nepal with 83.1 µg m⁻³ and Nigeria with 80.1 µg m⁻³, while the least pollution per capita exposure is below 8 µg m⁻³ (Pandey *et al.*, 2021) reported that in 2019 about 1.7 million deaths in India were due to air pollution which is 18% of the total deaths in the country, which in turn led to an economic loss due to lost output from premature deaths and morbidity. It is estimated to be 1.4% of the country's GDP; this loss in terms of state GDP was highest for Uttar Pradesh (2.2% of GDP) and Bihar (2% of GDP). The study also found that the death rate in India from outdoor ambient air pollution from 1990 to 2019 has increased by 115%.

In December 2019, the COVID-19 virus (Ciotti *et al.*, 2020), a rare pneumonia of unknown origin, was reported in Wuhan, Hubei Province, China. Subsequently, the disease spread to more Provinces in China and the rest of the world. India reported its first case on 27th January, 2020 in the state of Kerala (Andrews *et al.*, 2020), and spread across the country at a very high pace, causing a countrywide health emergency. As per the study conducted in the United States of America, COVID-19 is related to reduced levels of pollution, especially NO₂ (Berman & Ebisu, 2020). In many countries, the lockdown approach is used to control the spread of COVID-19; the lockdown strategy is basically to shut down economic and social activity and to impose social distancing with varying degrees of strictness. Globally, in many countries, the lockdown impacted the air quality to a greater extent, *e.g.*, in Spain, atmospheric levels of NO₂, CO, SO₂ and PM₁₀ decreased. Still, on the other hand, Ozone levels increased (Briz-Redón *et al.*, 2021). In Korea, it is found that the level of PM_{2.5}, PM₁₀, NO₂ and CO is reduced during lockdown (Ju *et al.*, 2021). Considering the meteorological parameters, lockdowns have reduced the population-weighted level of NO₂ and particulate matter by about 60% and 31% in 34 countries (Venter *et al.*, 2020).

The relationship between pollution levels and meteorology is a well-established fact. In Pantnagar, India, (Banerjee *et al.*, 2011) studied the relationships between Pollutants and meteorological parameters, and it was found that NO₂ and Total Suspended Particulate Matter (TSPM) concentrations are by meteorological variables with a coefficient of determination (R^2) of 82.21 and 92.84%, respectively. However, atmospheric SO₂ revealed only 22.87% of dependencies on meteorological variables. Regionally, a similar kind of

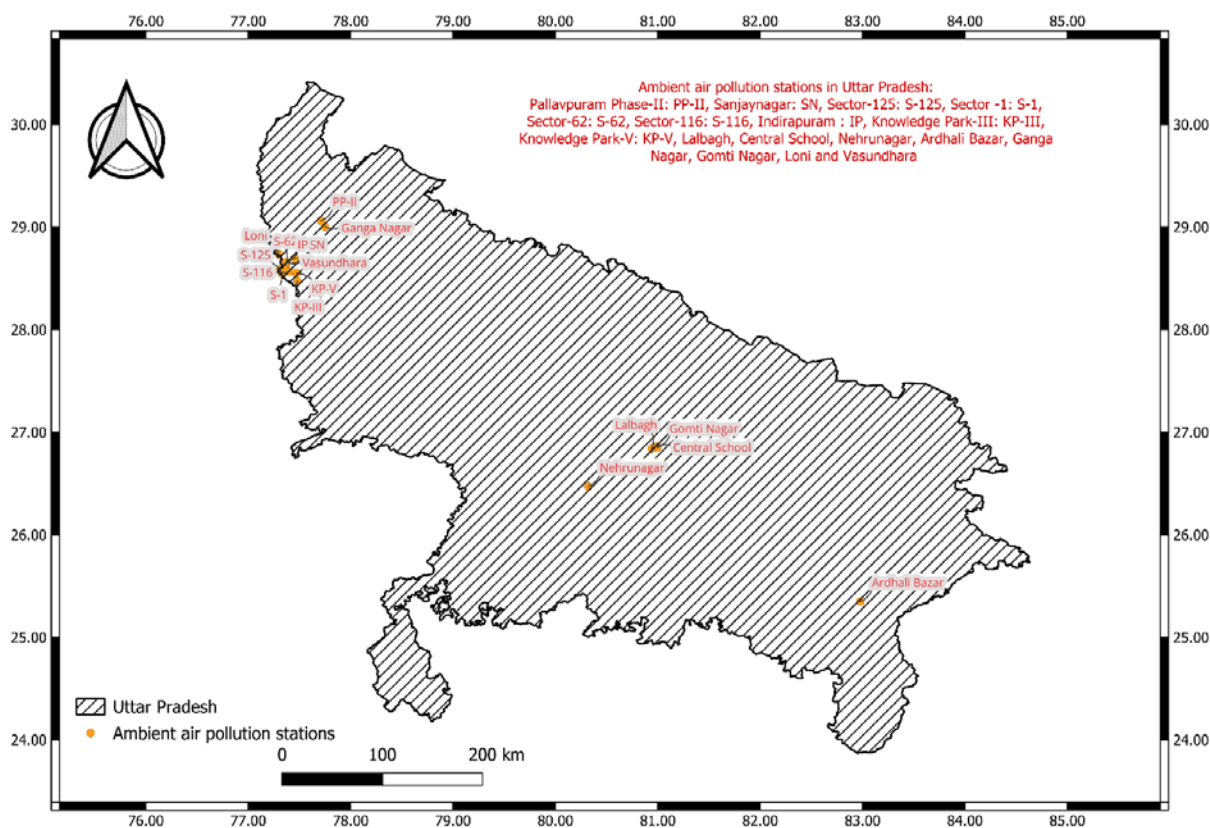


Fig. 1. The map of Uttar Pradesh, highlighting active sites for data collection

study is conducted in Ahmedabad by (Bhaskar *et al.*, 2010) and in Chandigarh by (Ravindra *et al.*, 2022) to understand the inter-relation between pollutants and meteorology. The seasonality of pollution level is also attributed to meteorology in a case study of Delhi (Guttikunda & Gurjar, 2012). Also, a drastic change in the meteorology of Delhi due to air pollution caused by the Deepawali Festival is observed (Saha *et al.*, 2014). Recently During the COVID-19 period, few nationwide studies suggest a significant relationship is found between COVID-19 infections, pollution levels and meteorological variables (Kolluru *et al.*, 2021; Sahoo, 2021). The COVID-19 virus affected almost every country, and many loss of lives were claimed due to its severity. In India, it entered on 27th January, 2020 and started creating havoc; it was taken into control using the Lockdown approach given into the next paragraph.

To control the first wave of COVID-19 in the country, the Indian government imposed a nationwide lockdown on 25th March, 2020 in a four-phased manner. It ended on 31st May, 2020 and from 1st June unlock phase started in which relaxations were given for economic and other activities. COVID-19 hit the country again in 2021 in the form of a second wave, which turned out to be a

tsunami. This wave resulted in a statewide lockdown from 5th April until 15th June, 2021 in many states of the country (Wikipedia, 2022). In the Kolkata district, a significant decrease in CO, NO₂ and SO₂ levels is observed, while a slight increase in Ozone level is also observed and pollution from particulate matter decreased by around 17.5% during the lockdown (Bera *et al.*, 2021). In a multi-district study by (Sathe *et al.*, 2021) in India with surface and satellite data enumerated, a 42-60% reduction in PM_{2.5} level and 46-61% in NO₂ level reduction was achieved during the lockdown. Further, AQI (Air Quality Index) is improved to level 21-56%, which can be considered significant in drafting a new AQI policy. In Delhi and Mumbai, the NO₂ level decreased by around 40-50% during the lockdown in contrast to the year 2019 for the same period (Shehzad *et al.*, 2020).

In the present study, an in-depth multi-temporal, spatial analysis of pollution levels in the COVID-19 period is done for the state of Uttar Pradesh. This study considers seven large cities with all available ground stations. The study timeline extends from 2019 to 2021, covering two massive waves of COVID-19 in 2020 and 2021, respectively. The data acquired in 2019 is used for a comparative analysis of air quality with that of the year

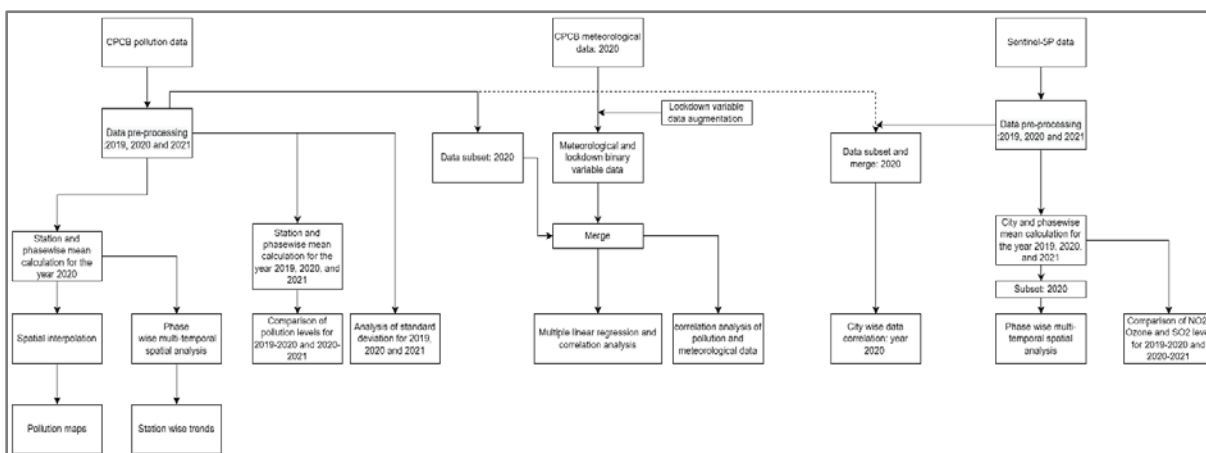


Fig. 2. The flow diagram of the methodology used

2020, whereas the data obtained in 2020 is used for a precise multi-temporal analysis of air quality during the lockdown period. The timeline for the COVID-19 lockdown imposed in 2020 has been divided into six phases which are named PL: pre-lockdown (1st Jan-24th Mar, 2020), P₁: lockdown phase-1 (25th Mar-14th Apr, 2020), P₂: lockdown phase-2 (15th Apr-3rd May, 2020), P₃: lockdown phase-3 (4th May-17th May, 2020), P₄: lockdown phase-4 (18th May-31st May, 2020) and UL: unlock phase (1st Jun-31st Dec, 2020). This timeline is also used for 2019 and 2021 as a reference for an effective phase-wise comparison.

2. Data set used

2.1. Ground station pollution data

The 24-hour atmospheric pollution data for 2019, 2020 and 2021 are downloaded from the central pollution control board (CPCB) portal, regulated by the government of India for providing free data. There are 17 sites in the study area, *i.e.*, the state of Uttar Pradesh, India, which were active throughout the study time period and covered six districts of the state, *viz.*, Gautam Budh Nagar, Ghaziabad, Meerut, Lucknow, Kanpur and Varanasi, which are shown in Fig. 1 with yellow dots. The operational stations are located at Sector-1, Sector-62, Sector-116, Sector-125, Knowledge Park-III and V in Gautam Budh Nagar district; Sanjaynagar, Loni, Vasundhara and Indirapuram in Ghaziabad district; Pallavpuram Phase-II and Ganga Nagar in Meerut district; Nehru Nagar in Kanpur; Gomti Nagar, Central School and Lalbagh in Lucknow district and Ardhali Bazar in Varanasi district. The ground stations collect data for various pollutants, including PM_{2.5}, PM₁₀, NO₂, NO_x, NO, SO₂ and Ozone. The active station count is lower for the year 2019 as compared to the years 2020 and 2021. The

unit for all pollutants levels is $\mu\text{g}/\text{m}^3$ except for NO_x, which is parts per billion (ppb).

2.2. Ground station meteorological data

All the stations deployed by CPCB disburse meteorological data as well as various parameters like temperature (Temp), relative humidity (RH), wind speed (WS), and air temperature (AT). The meteorological data for 2020 are also downloaded from the CPCB portal for regression and correlation analysis in harmony with pollution data.

2.3. Satellite data

Time series data for pollutants NO₂, SO₂ and Ozone are obtained from Sentinel-5P (S5P) data, for which the onboard sensor is known as the Tropospheric Monitoring Instrument (TROPOMI). The S5P satellite was launched on 13th October, 2017 by the European Space Agency (ESA) to monitor air pollution with a spatial resolution of $7 \times 7 \text{ km}^2$ (de Vries *et al.*, 2016). All S5P data sets except for CH₄ have two types: real-time (NRTI) and offline (OFFL). However, only level 3 OFFL data is retrieved using Google Earth Engine and related shape files for the present study. The three pollutants measured using S5P data are TROPOMI NO₂, TROPOMI SO₂ and TROPOMI Ozone, estimated by their column number density values.

3. Methodology

The methodology is shown in Fig. 2, which works in 3 parallel pathways where the data of three different kinds are processed for a multilevel pollutant analysis. The first route is used for ground station pollution data, the second for meteorological data, and the third for satellite data. Further, the outcomes of these routes are used together for

correlative studies. The steps involved are described in the following subsections.

3.1. *Data pre-processing*

The first step of the methodology is preprocessing of the data, which has been done in two folds.

3.1.1. *Pre-processing of ground station pollution data*

The time series data is available in tabular form, which contains gaps or missing data due to a sensor down or any other unexpected situations. Therefore, for effective analysis, the gaps must be filled, or the missing data must be taken into account by using interpolated data. The preprocessing of ground station data refers to the recovery of missing data for which linear interpolation imputation has been applied. After preprocessing in this manner, the time series data becomes complete for further analysis.

3.1.2. *Pre-processing of satellite data*

The S5P raster data is processed using Google Earth Engine (GEE) (Mutanga & Kumar, 2019) by importing the required data collections with a timeline filter with the application of shape files of the study areas; selecting the data in this manner generates a time series chart, which is downloaded in tabular form in comma separated values (CSV) format. The downloaded CSV files have a few duplicate values, which are removed by filtering the data further.

3.2. *Spatial interpolation*

There are 80 districts in Uttar Pradesh, but sensors are not deployed at all locations; only a few major cities have the data procurement capacity. A spatial interpolation scheme named Inverse Distance Weighted (IDW) (Mueller *et al.*, 2004) is used to get approximated pollution maps for all the locations of the state; this scheme is applied to all the pollutants. IDW calculates cell values using linearly weighted combinations of a set of sample points, where weight is an inverse function of distance. The interpolated surface, thus obtained, must be a location-dependent variable. The formula for IDW is given in equation (1).

$$Z_p = \frac{\sum_{i=1}^n \left(\frac{Z_i}{d_i^p} \right)}{\sum_{i=1}^n \left(\frac{1}{d_i^p} \right)} \tag{1}$$

Where d_i is the distance of the interpolated location from the known location, z_i is the value of the known location, and order p controls the value of the interpolated point on the basis of the known location point.

3.3. *Phase-wise multi-temporal spatial analysis*

In this step, the percentage change of pollution level over the phases for 2020 is calculated by taking the PL phase as the reference. In addition, the effect of phase-wise COVID-19 lockdown is estimated to stem air pollution. The formula for calculation is given in equation (2), where μ_{PL} is the mean of phase PL , μ_{Pi} is the mean for subsequent phases and Δ_i is the calculated change.

$$\Delta_i = \frac{(\mu_{PL} - \mu_{Pi})}{\mu_{PL}} \times 100 \tag{2}$$

3.4. *Comparison of pollution levels for 2019-2020 and 2020-2021*

In this step, the percentage change in pollution level is calculated by taking 2019 as a reference for 2020 and 2020 as a reference for 2021 according to the timeline described in Section 1. The comparison formulas are given in equations (3) and equation (4), where μ_{2019Pi} , μ_{2020Pi} and μ_{2021Pi} are mean pollution levels for phases P_i , $\Delta_{19-20Pi}$ and $\Delta_{20-21Pi}$ are the calculated percentage change.

$$\Delta_{19-20Pi} = \frac{\mu_{2019Pi} - \mu_{2020Pi}}{\mu_{2019Pi}} \times 100 \tag{3}$$

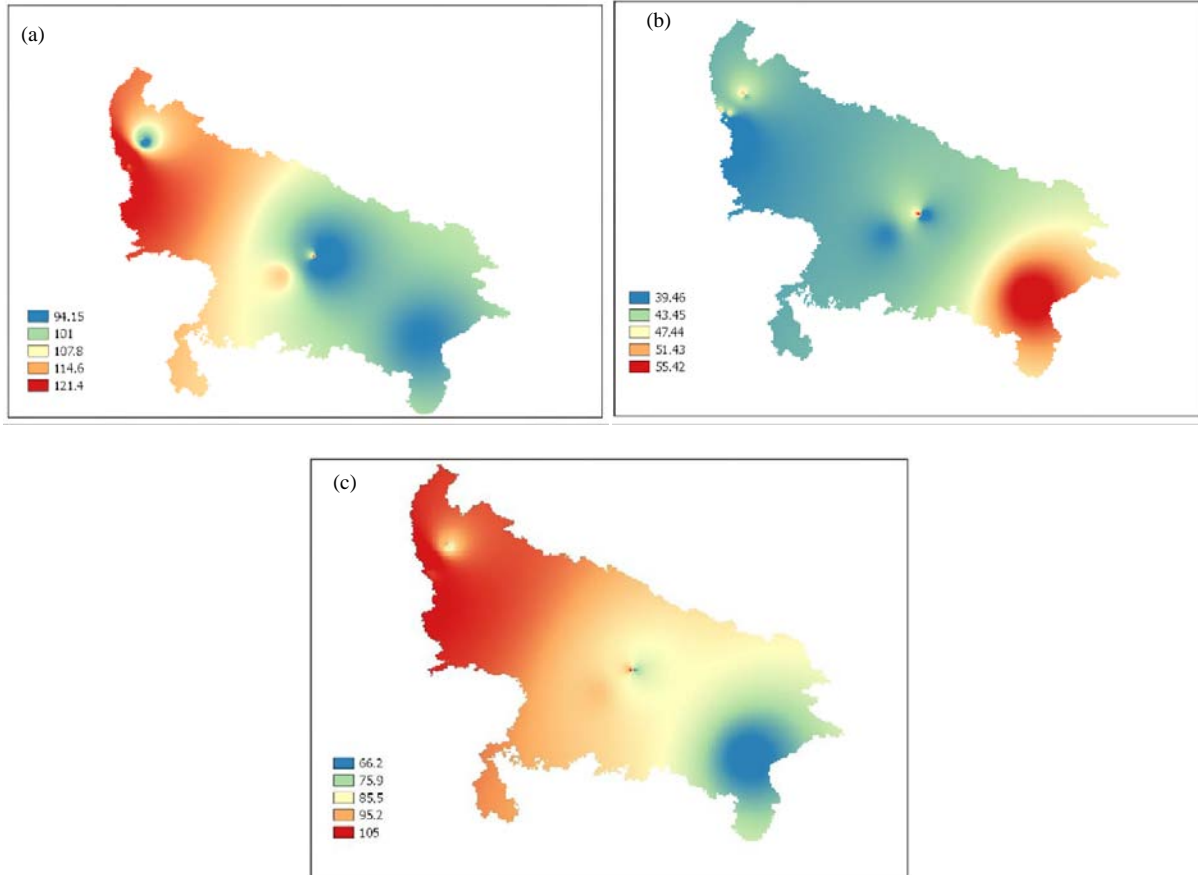
$$\Delta_{20-21Pi} = \frac{\mu_{2020Pi} - \mu_{2021Pi}}{\mu_{2020Pi}} \times 100 \tag{4}$$

Further, the standard deviation (σ) is calculated to analyse the variation of pollution level for the years 2019, 2020 and 2021 in the lockdown period, *viz.*, during phase P_1 through phase P_4 . The formula for standard deviation is given in equation (5).

$$\sigma = \sqrt{\frac{\sum (P_{ij} - \bar{P}_i)^2}{n-1}} \tag{5}$$

where P_{ij} is the j^{th} observation of the i^{th} pollutant and P_i is the mean value of the i^{th} pollutant and n is the total number of observations.

The phase-wise spatial analysis and comparison of pollution levels for the years 2019-2020 and 2020-2021 described in Sections 3.3 and 3.4 are also applied to S5P data. The satellite-based results are expected to produce



Figs. 3(a-c). Spatial interpolation: PM_{2.5} (a): PL, (b): P1 and (c): UL

authentic results which are at par with the ground data-based results.

3.5. Correlation between ground and Satellite data

In this step, district-wise data from ground stations and data from satellites are used to calculate the Pearson correlation coefficient (r) for NO₂, Ozone and SO₂. The formula is given in equation (6).

$$r_{xy} = \frac{\sum_{i=1}^n (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^n (x_i - \bar{x})^2} \sqrt{\sum_{i=1}^n (y_i - \bar{y})^2}} \quad (6)$$

where n is the total number of observations, x_i and y_i are i^{th} observations of x , y respectively and \bar{x} , \bar{y} are the mean values of x , y respectively.

3.6. Multiple linear regression (MLR)

Before performing the method given below, augmented data is generated after merging meteorological

data with binary lockdown variables $P_1 - P_4$ column-wise; these variables have values 0 or 1. The augmented data is combined with pollution data column-wise to fulfill the dependent and independent variables required for the regression method given below. Multiple linear regressions (Tranmer & Elliot, 2008) are an extension of the linear regression method involving more than one input variable and one output. The formulation for multiple linear regressions is given in equation (7).

$$Y = C + \sum_{i=1}^n \alpha_i X_i \quad (7)$$

Where Y is the output variable, C is a constant intercept, α_i are slope coefficients, and X_i are input variables. Based on equation (7), a regression model is generated with augmented data as independent and pollution data as dependent variables; it is shown in equation (8), where Y is the pollution level, C is the calculated constant intercept, m_i are meteorological variables, P_j are binary lockdown variables and α_i , β_j are calculated slopes.

$$Y = C + \sum_{i=1}^n \alpha_i m_i + \sum_{j=1}^n \beta_j P_j \quad (8)$$

4. Results

4.1. Spatial interpolation

The pollution maps generated from IDW interpolation are divided into six analysis phases, as mentioned in Section 1. Pollution maps' significance is visually analysing the pollution level throughout the state. The variation of different pollutants has been highlighted through pollution maps, which indicate the minimum and maximum value of individual pollutants. Since each district has not been provided with a ground observation station, the pollution map offers a glimpse of pollution throughout the state. For the sake of brevity, only 3 phases, *viz.*, PL, P₁ and UL, are shown for visual analysis using pollution maps. The pollution maps corresponding to PM_{2.5} are shown in Fig. 3. Spatial interpolation: PM_{2.5} (a): PL, (b): P₁, (c): UL, where the subfigures (a) through (c) correspond to PL, P₁ and UL phases, respectively. Similarly, the pollution maps for other pollutants, *viz.*, PM₁₀, NO₂, NO_x, NO, SO₂ and Ozone, are also generated and used for the analysis.

The pollution maps of PM_{2.5} is shown in Fig. 3; the values range between 94.15 and 121.4 during the PL phase [Fig. 3(a)], between 39.46 and 55.42 during the P₁ phase [Fig. 3(b)] and between 66.2 and 105 during UL phase [Fig. 3(c)]. Similarly, pollution maps for other pollutants are generated (not displayed in the figure) and analysed. The pollution maps of PM₁₀ depict the pollution level of PM₁₀ ranging between 196.1-208.3, 109.9-121.1 and 201.5- 209.4 in PL, P₁ and UL, respectively. The pollution maps for NO₂ have the pollution level of NO₂ ranging between 35.6-55.3, 14.5-31 and 32.3-54.2 in PL, P₁ and UL, respectively. The pollution maps of NO_x have the pollution level for NO_x ranging between 18.2-44.2, 9.21-14.7 and 18.9-45 in PL, P₁ and UL, respectively. Further, the pollution maps of NO, SO₂ and Ozone possess the pollution levels of NO ranging between 9.91-19.7, 3.25-8.53 and 12.4-22.2, that of SO₂ between 9.9-18.1, 9.15-30.4 and 8.76-18.5 and that of Ozone between 23.5-45.4, 32.32-46.87 and 25.4-43.3 in PL, P₁ and UL phases respectively.

Talking about pollutants specifically, due to decreased or stopped human and industrial activities, pollution levels due to particulate matters like PM₁₀ and PM_{2.5} have drastically reduced during the lockdown; similarly, pollution levels due to pollutants NO₂, NO and NO_x have decreased significantly due to lesser or no vehicular transport during the lockdown period. During

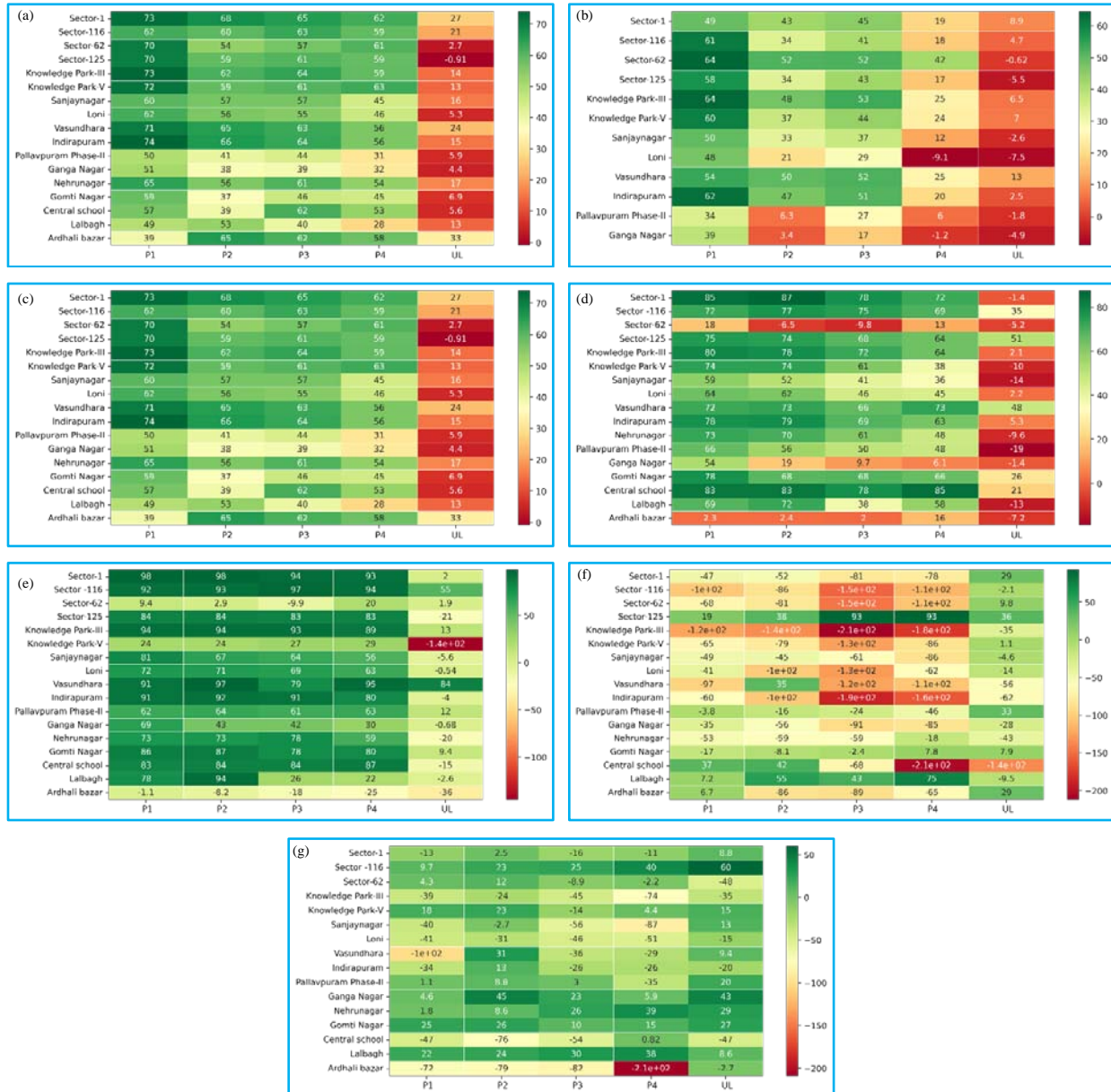
the lockdown, although all the activities were shut down, the Ozone level increased due to the hot summer in which the Ozone is mainly produced when pollutants emitted by cars, power plants, industrial boilers, refineries, chemical plants, and other sources chemically react in sunlight. For the pollutant SO₂, the pollution level has decreased in its lower limit, and an increase in the upper limit is observed. In contrast, the pre-lockdown pollution level is nearly recovered after the lockdown. However, we are unsure about the clear-cut reason behind this unusual pattern. Still, it might be due to some unnoticed industrial activities, where the burning of fossil fuels in power plants or other industrial facilities was taking place.

It is evident from the analysis of pollution maps that during the lockdown phase, pollution decreased due to low human and industrial activities. After the lockdown, the level of most of the pollutants under study has started increasing. It is also to be noted that for certain pollutants, the maximum level during lockdown has been crossed by the minimum level immediately after lockdown. This fact seems alarming as human activities started more drastically after the lockdown, which was suppressed during the lockdown period. The probable reasons for such a change may include social and economic aspects; however, they are not considered in the present study. Further, only ground station points have been considered for the rest of the analysis instead of pollution maps.

It is also worth noting that these pollution maps are made using only 17 active stations, which is not sufficient for giving the most accurate interpolation results, but using only this much data for pollution maps provides us with an insight into pollution levels over the state, as IDW works based on the distance and interpolation order, it makes sure that the points which are far away from available stations do not get affected much, however, these points tend to give weightage to the stations which are comparatively in the closer proximity. As we have seen the active station map in Fig. 1, there are so many stations around Gautam Budh Nagar, Ghaziabad, Meerut, and Lucknow but only two stations in Kanpur and Varanasi Combined. When interpolation starts working, regions around Kanpur and Varanasi give weightage to Lucknow and themselves more than that of Ghaziabad, Gautam Budh Nagar, etc. and *vice versa*. In this way, the impact of clusters is reduced in the overall interpolated maps.

4.2. Phase-wise multi-temporal spatial analysis for the year 2020

In this section, a phase-wise analysis of pollution level for all seven cities, along with all the stations, are done. The analysis is divided into six phases mentioned in



Figs 4(a-g). Phase-wise transition for the year 2020, (a): $PM_{2.5}$, (b): PM_{10} , (c): NO_2 , (d): NO_x , (e): NO , (f): Ozone and (g): SO_2

Section 3.3 such that the PL phase is used as a base to draw the contrast against subsequent phases highlighted in equation (4). A positive value shows a decreased level of pollution, whereas a negative value represents an increased level of pollution, corresponding to the PL phase. The complete phase-wise transition is shown in Figs. 4(a-g). The colour code, red to green, in Fig. 4 represents a scale from low to high values.

It is observed from Fig. 4(a) that in phase P₁, represented by the first column of the figure, the stations Indirapuram (74%) and Ardhali Bazar (39%) show the maximum and minimum improvement in the level of

$PM_{2.5}$. The data state that there is a change of 74%, *i.e.*, improvement in the air quality due to the decrease in $PM_{2.5}$ at Indirapuram, which is the maximum change in phase P₁ against phase PL. At the same time, the minimum change of 39% is observed at Ardhali Bazar during P₁, which shows a significant improvement in air quality despite being the minimum value of the column. Similarly, the changes corresponding to phase P₂, shown in the second column of the figure, are observed at Sector-1 (68%) as the maximum and Gominagar (37%) as the minimum. Further, for phase P₃, Sector-1 (65%) and Ganganagar (39%); for phase P₄, Knowledge Park-V (63%) and Lalbagh (28%); and for phase UL, Ardhali

Bazar (33%) and Sector-125 (-0.91%) show maximum and minimum improvements which are represented in third, fourth, and fifth columns respectively. The minimum change at Sector-125 shows a negative value which represents that the level of $PM_{2.5}$ is increased in the UL phase as compared to the PL phase, *i.e.*, the air quality at the station has slightly degraded in the UL phase.

In the phase-wise transition shown in Figs. 4(b-e), the number of observations linked with increased pollution levels is 8, 9, 11, and 15 for PM_{10} , NO_2 , NO_x , and NO respectively; these observations with increasing pollution level are mostly centred around P_4 and UL except few {Citation} stations, which ascertain the increase in pollution level towards the end of study timeline in comparison with phase PL. Since most of the observations for the aforementioned pollutants show decreased pollution levels, an overall decrease in pollution levels is noticed. In order of phase-wise improvements, except for PM_{10} , the phases are ranked as P_1 , P_2 , P_3 , P_4 , and UL from higher to lower. Accordingly, in Figs. 4(f&g), with over 64 observations linked with increased pollution level, Ozone shows a steep rise in pollution level and with 38 similar observations SO_2 also showed an overall increased level of pollution.

4.3. Phase-wise comparison of pollution level

In this step, phase-wise change in the pollution level of the pollutants is estimated as indicated by equations (5) and (6). The results emphasise the increment or decrement in pollution levels during PL-UL phases and are represented in percentages. The PL-UL phases here represent common comparative timelines for the years 2019, 2020 and 2021. For the sake of preciseness, phases $P_1 - P_4$ are used as a unit phase.

4.3.1. Comparison of pollution levels of the year 2020 with 2019

The pollution level noticed in 2020 is lower than the observation pertaining to 2019 for all the pollutants. A brief analysis of each pollutant is now described and the most affected stations are identified. In the $PM_{2.5}$ transition from 2019 to 2020, most of the observations showed a decreased pollution level except Lalbagh in PL and Central School, Knowledge Park-III, Lalbagh, Loni, Nehrunagar, Sector-125, and Sector-62 in the UL phase. The pollution level during P_1-P_4 noticed a significant decrease for all the stations, out of which Ardhal Bazar showed maximum improvement with (55.44%), and Lalbagh showed minimum improvement with (23.12%) in pollution level. As the common stations between 2019 and 2020 are 11, the total observation through three phases, PL, P_1-P_4 and UL phase, are 33 in number. At the same

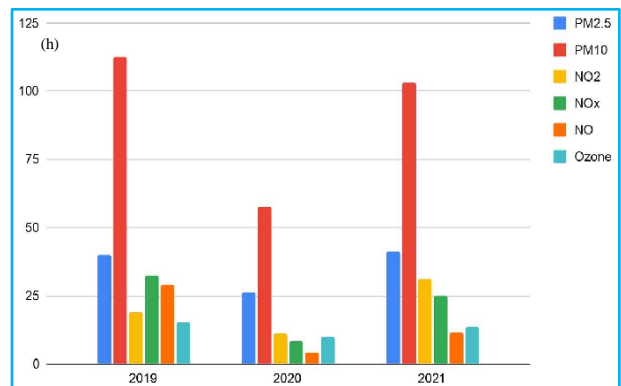
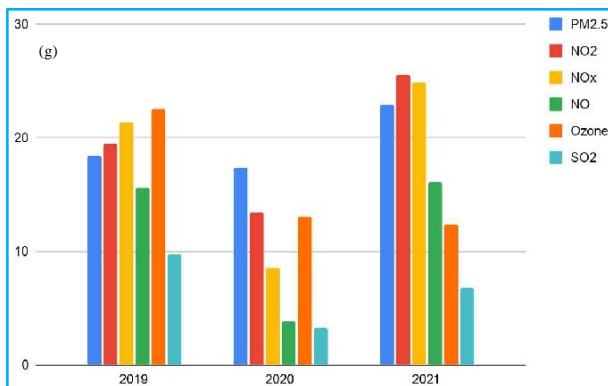
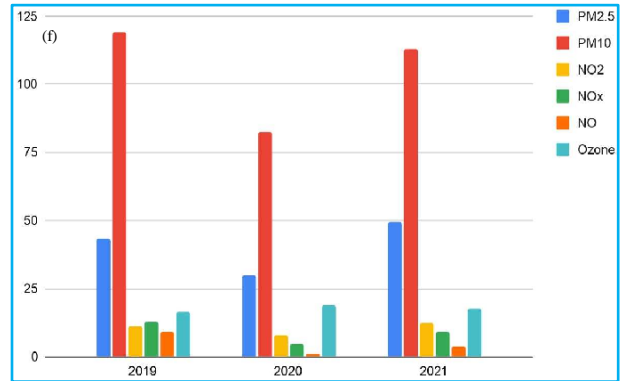
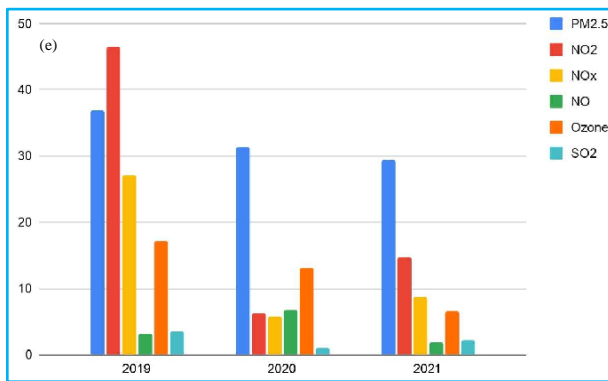
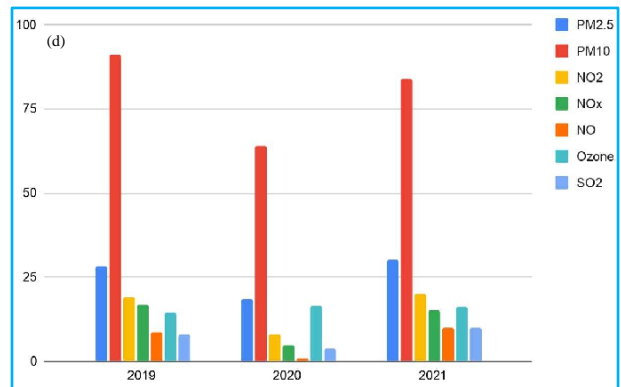
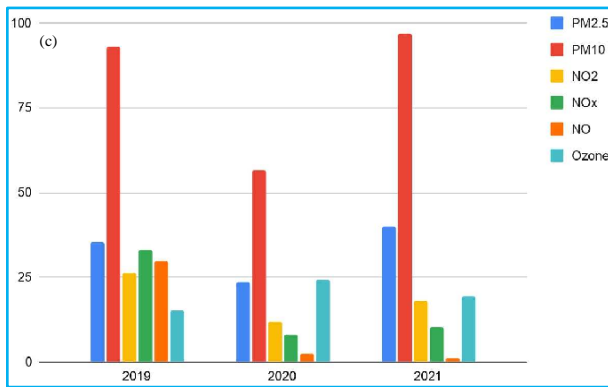
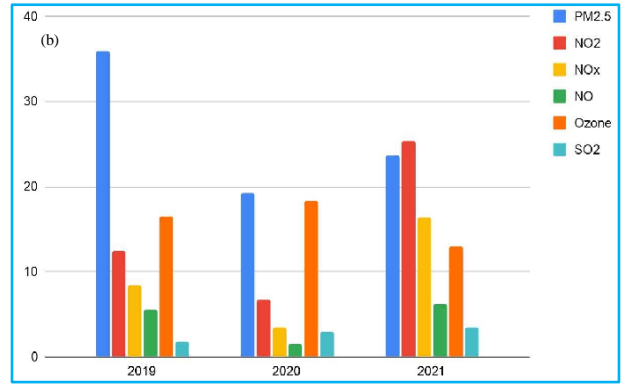
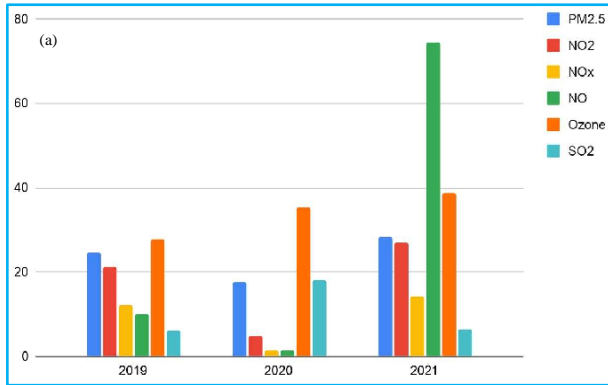
time, the commonly available stations for SO_2 are 7, with 21 total observations. Accordingly, with over only 3, 6, 6, and 8 observations linked to increased pollution levels for PM_{10} , NO_2 , NO_x and NO, the overall pollution level for these pollutants decreased significantly. The point worth noticing is that the increment in pollution level for the aforementioned pollutants is limited to the phases PL and UL. Similarly, for Ozone, 5 observations each in PL, P_1-P_4 and UL showed an increased pollution level, and the rest of the observations showed a decrease in pollution level. Likewise, for SO_2 , 3 observations in PL, 2 observations in P_1-P_4 and 4 observations in UL showed increased levels of pollution, while the rest of the observations showed decreased pollution levels. In a major context, 6 out of 11 stations measuring Ozone showed increased levels, while 3 out of 7 stations measuring SO_2 showed increased pollution levels.

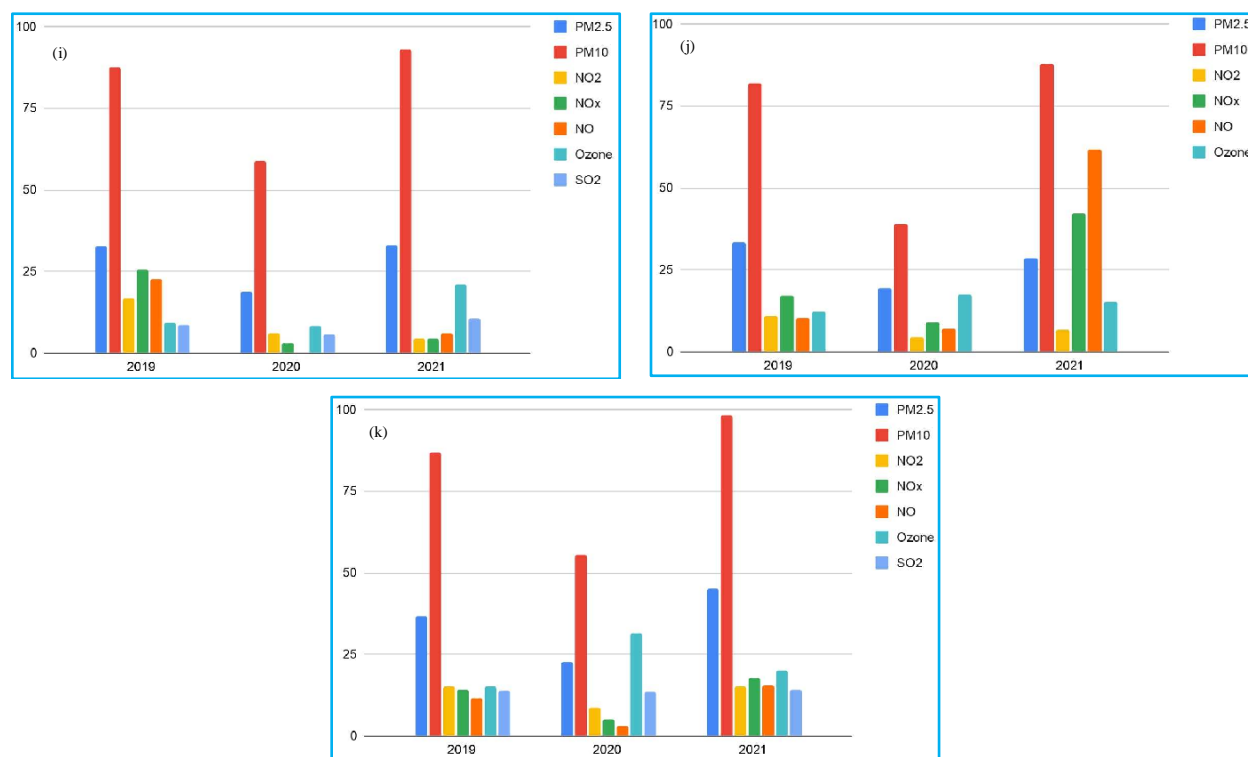
4.3.2. Comparison of pollution levels of the year 2021 with 2020

A brief overview of the pollution level transition during 2020-2021 is given. The $PM_{2.5}$ level in 2021 has increased in all the observations of PL and P_1-P_4 except at Lalbagh in P_1-P_4 , while in UL pollution level has decreased in all the observations. Similarly, the PM_{10} level has increased in all the observations of PL and P_1-P_4 and in 4 out of 11 observations of UL. Similarly, in NO_2 observations, the pollution level has increased at all the observations except 5 observations of PL, 1 observation during P_1-P_4 and 10 observations of UL. In a major context, the pollution level in UL due to NO_2 decreases, while for other phases increases. Likewise, NO_x level has increased everywhere except 5 observations of PL, and 3 observations of UL, while during P_1-P_4 , all the observations showed a significant increment in pollution level. Similarly, the NO level has increased in all the observations except at 7 observations of PL and UL and 1 observation during P_1-P_4 . For Ozone, nearly equal observations through PL, P_1-P_4 , and UL showed both increment and decrement in pollution level, leaving no significant trend. Similarly, for SO_2 , only 5 observations of PL and UL and 3 observations during P_1-P_4 showed a decrease in pollution level, giving a trend of overall increment in SO_2 level.

4.3.3. Analysis of mean and standard deviation during P_1-P_4

Ground data from all available common stations for the years 2019, 2020 and 2021 are used to analyse the standard deviation during the lockdown period, *i.e.*, P_1-P_4 . For graphical interpretation of standard deviation, column graphs are drawn for available pollutants, which are given in Fig. 5. It is worth mentioning that the data of





Figs. 5(a-k). Standard deviation during P1-P4: 2019, 2020 and 2021 (a): Ardhali Bazar, (b): Central School, (c): Indirapuram, (d): Knowledge Park-III, (e): Lalbagh, (f): Loni, (g): Nehrunagar, (h): Sanjaynagar, (i): Sector-125, (j): Sector-62 and (k): Vasundhara

all pollutants are not available at each ground station, which is reflected in the column graph of individual stations. The analysis based on Fig. 5 suggests that in comparison with 2019, the standard deviation in 2020 observations is reduced significantly for almost all the pollutants except Ozone, which has increased in most of the observations, while in comparison to 2020, standard deviation values in 2021 increased for almost all the observations except Ozone, which majorly does not hold any increasing or decreasing trend.

4.4. Phase-wise multi-temporal spatial analysis for Sentinel-5P

The phase-wise transition for satellite pollution data is calculated using equation (4); the transition is used to recognise the improvements in pollution levels for six districts, out of which the districts and phases linked with maximum and minimum improvements are highlighted below.

The observations for NO₂ pollution suggest that the NO₂ pollution level in Gautam Budh Nagar has shown the maximum improvement through all the phases, while Varanasi in P₁, P₃ and UL and Meerut in P₂ and P₄ have shown the least improvement. As per Ozone observations, in P₁, a slight increase is recorded for all the cities; in

P₂ and P₃, a slight decrease is observed for Ghaziabad and Meerut; in P₄ and UL, a decrease of less than 10% is recorded through all the cities. Similarly, for SO₂ observations, Varanasi in P₁ and P₃, Meerut in P₂, Kanpur in P₄, and Lucknow in UL have shown the maximum improvement, while Gautam Budh Nagar in P₁ and UL, Ghaziabad in P₂ and P₄, and Lucknow in P₃ has shown the least improvement respectively. On the whole, these phase-wise transitions, by and large, suggest the enormity of decreased NO₂ and SO₂ levels and a slight increase and decrease in Ozone levels.

4.5. Phase-wise comparison of pollution level for Sentinel-5P

This step is divided into two parts; in the first part, satellite observations of 2020 are compared with 2019, and in the second part, observations of 2021 are compared with 2020. The estimated analysis is given in the below subsections.

4.5.1. Comparison of pollution levels of the year 2021 with 2020

The phase-wise transition for satellite pollution data between 2019 and 2020 is calculated using equation (5); this transition is used to investigate the changes in

pollution level for the six districts. In NO₂ transitions from 2019 to 2020, all the observations showed decreased pollution levels, out of which phase PL seems the most significant, while UL seems least significant. Comparatively, Ghaziabad (43.20%) in PL, Gautam Budh Nagar (37.59%) during P₁-P₄ and Ghaziabad (27.70%) in UL showed the maximum improvement, while Meerut (17.06%) in PL, Varanasi (10.19% and 7%) during P₁-P₄ and UL showed minimal improvement in pollution levels. Similarly, Ozone observations showed an increase of less than 12.27% in PL and 5.32% during P₁-P₄ for all the districts. Moreover, all the observations in UL showed a slight increase in the level of pollution. For SO₂ observations, districts Gautam Budh Nagar and Ghaziabad in PL, Gautam Budh Nagar, Meerut, Lucknow and Varanasi during P₁-P₄, and Meerut and Lucknow in UL showed a significant decrease in pollution levels. Moreover, 8 out of 18 observations showed a decreased level of SO₂ level.

4.5.2. *Comparison of pollution levels of the year 2020 with 2019*

The phase-wise transition for satellite pollution data between 2020 and 2021 is calculated using equation (6); this transition is used to investigate the changes in pollution level for the six districts. Compared to 2020, in 2021, NO₂ transitions have seen a sharp increment in the level of contamination in all the observations. The maximum increment is seen for Ghaziabad (76.05%) in PL, Gautam Budh Nagar (60.22%) during P₁-P₄ and Ghaziabad (38.32%) in UL and the minimum increment is seen for Meerut (20.57%) in PL, Varanasi (11.35%) during P₁-P₄ and Lucknow (2.45%) in UL. Ozone transitions showed a decrease of less than 7.34% in PL and 1.79% during P₁-P₄, while observations in UL showed increased levels for all the districts. The SO₂ transitions showed pollution level increment for Gautam Budh Nagar and Ghaziabad in PL, Gautam Budh Nagar, Meerut, Kanpur, Lucknow and Varanasi during P₁-P₄ and Ghaziabad and Meerut in UL. Moreover, 9 out of 18 observations showed an increased level of SO₂.

4.6. *Validation of analysis*

In phase-wise multi-temporal analysis through 2020, only NO₂ pollution data from both the satellite and ground stations give similar trends of pollution level changes. Similarly, in the 2019-2020 transition, except for Lucknow in PL and UL and Kanpur in UL, the NO₂ transitions are similar for both satellite and ground data, while the observations for Ozone and SO₂ are found to be similar for only Gautam Budh Nagar. Likewise, in the 2020-2021 transition, Gautam Budh Nagar, Ghaziabad, and Meerut followed similar kind of observations in PL and P₁-P₄ and Kanpur, Lucknow and Varanasi showed

similar observations in all phases for NO₂, while for Ozone, and SO₂ the observations of ground and satellite are more or less converse of each other. The above analysis suggests that the NO₂ data from satellites are found to work in more harmony with ground station data than the other two pollutants.

4.7. *Correlation between ground and Satellite data*

In this section, data from the ground station and satellites are used to determine the strength of the relationship with Pearson's correlation coefficient (r). The NO₂ data correlation in Gautam Budh Nagar, Ghaziabad, Meerut and Kanpur are 0.72, 0.56, 0.65 and 0.42, respectively. At the same time, in Lucknow and Varanasi, these values are negative, and the Ozone correlation in Kanpur and Varanasi are 0.55 and 0.28, respectively. At the same time, in other places, they have very low values. The SO₂ correlation in Kanpur is 0.34, while it is very low at other places.

4.8. *Multiple linear regression-based analysis*

The MLR is used to derive an empirical relationship between pollution level (output) and augmented dataset (input); this procedure is repeated for each pollutant in a district-wise manner. This empirical relationship, with the available augmented data, can be used to regenerate pollution data. The multiple regression model, derived from equation (8) for actual parameters, is given in equation (9).

$$Y = C + \alpha_1 \times \text{Temp} + \alpha_2 \times \text{RH} + \alpha_3 \times \text{WS} + \alpha_4 \times \text{AT} + \beta_1 \times P_1 + \beta_2 \times P_2 + \beta_3 \times P_3 + \beta_4 \times P_4 \tag{9}$$

Here, α_1 - α_4 are estimated coefficients of meteorological variables, P₁-P₄ are binary lockdown variables, and β_1 - β_4 are estimated coefficients of binary lockdown variables. The multiple linear regression equations of Sector-125 for all 7 pollutants are given in equations (10) to (16), and for Knowledge park-V, the relationships are shown in equations (17) to (23). As no Temp data is available for Sector-125, the rest of the parameters are considered.

$$\text{PM}_{2.5} = 24.22 + 0.41 \times \text{RH} - 41 \times \text{WS} + 0.19 \times \text{WD} + 1.91 \times \text{AT} - 5.85 \times P_1 + 1.6 \times P_2 + 3.53 \times P_3 + 0.73 \times P_4 \tag{10}$$

$$\text{PM}_{10} = -77.8 + 0.52 \times \text{RH} - 55.77 \times \text{WS} - 0.37 \times \text{WD} + 8.76 \times \text{AT} - 16.96 \times P_1 + 6.09 \times P_2 - 6.75 \times P_3 + 17.61 \times P_4 \tag{11}$$

TABLE 1

Mean absolute error for station-wise multiple linear regression

	PM _{2.5}	PM ₁₀	NO ₂	NO _x	NO	Ozone	SO ₂
Sector 125	10.83	29.32	2.93	1.56	0.05	2.56	3.41
Sector-1	11.8	25.51	2.66	1.68	0.49	6.04	1.04
Sector-116	12	23.3	4.51	2.83	1.03	10.92	3.3
Knowledge Park-V	9.32	28.11	3.09	1.97	0.5	8.44	1.88
Indirapuram	14.08	26.37	5.26	3.37	1.01	9.38	5.66
Loni	18.16	37.34	4.38	2.64	0.56	11.72	3.44
Sanjaynagar	14.68	24.2	4.4	3.5	2.01	6.62	3.56
Vasundhara	13.63	22.39	4.85	3.12	2.2	15.61	7.88
Ganga Nagar	13.35	33.57	2.65	1.64	0.36	2.38	2.11
Pallavpuram Phase-II	15.57	45.7	5.03	3.49	1.3	3.02	3.5
Nehrunagar	9.81	-	5.44	3.95	2.81	8.72	2.02
Central School	12.1	-	4.39	2.4	1.01	5.99	2.05
Gomti Nagar	7.06	-	2.64	1.86	1.07	5.82	1.91
Lalbagh	19.29	-	3.63	3.2	3.28	6.41	0.57
Ardhali Bazar	10.58	-	2.33	0.74	0.77	20.66	9.38

$$\text{NO}_2 = 54.59 - 0.25 \times \text{RH} - 7.02 \times \text{WS} - 0.09 \times \text{WD} - 0.55 \times \text{AT} - 4.52 \times \text{P}_1 - 1.21 \times \text{P}_2 - 1.45 \times \text{P}_3 + 7.18 \times \text{P}_4 \quad (12)$$

$$\text{NO}_x = 26.52 - 0.10 \times \text{RH} - 4.04 \times \text{WS} - 0.02 \times \text{WD} - 0.21 \times \text{AT} - 2.21 \times \text{P}_1 - 0.9 \times \text{P}_2 - 0.45 \times \text{P}_3 + 3.56 \times \text{P}_4 \quad (13)$$

$$\text{NO} = -2.21 + 0.03 \times \text{RH} - 0.56 \times \text{WS} + 0.03 \times \text{WD} + 0.09 \times \text{AT} + 0.15 \times \text{P}_1 - 0.23 \times \text{P}_2 + 0.34 \times \text{P}_3 - 0.26 \times \text{P}_4 \quad (14)$$

$$\text{SO}_2 = 35.78 - 0.18 \times \text{RH} - 7.52 \times \text{WS} - 0.07 \times \text{WD} - 0.07 \times \text{AT} - 1.45 \times \text{P}_1 - 0.55 \times \text{P}_2 + 0.22 \times \text{P}_3 + 1.77 \times \text{P}_4 \quad (15)$$

$$\text{Ozone} = 28.22 - 0.10 \times \text{RH} - 0.73 \times \text{WS} + 0.04 \times \text{WD} - 0.41 \times \text{AT} + 7.21 \times \text{P}_1 + 5.57 \times \text{P}_2 - 5.22 \times \text{P}_3 - 7.56 \times \text{P}_4 \quad (16)$$

$$\text{PM}_{2.5} = 174.93 - 6.19 \times \text{Temp} - 0.12 \times \text{RH} - 9.68 \times \text{WS} + 0.03 \times \text{WD} + 2.48 \times \text{AT} - 1.81 \times \text{P}_1 + 2.58 \times \text{P}_2 - 0.53 \times \text{P}_3 - 0.24 \times \text{P}_4 \quad (17)$$

$$\text{PM}_{10} = -357.23 + 2.46 \times \text{Temp} - 0.86 \times \text{RH} + 2.57 \times \text{WS} + 0.25 \times \text{WD} + 12.34 \times \text{AT} - 3.36 \times \text{P}_1 + 10.03 \times \text{P}_2 - 15.8 \times \text{P}_3 + 2.41 \times \text{P}_4 \quad (18)$$

$$\text{NO}_2 = -24.12 + 2.46 \times \text{Temp} - 0.19 \times \text{RH} - 3.44 \times \text{WS} - 0.02 \times \text{WD} - 0.15 \times \text{AT} - 6 \times \text{P}_1 - 2.25 \times \text{P}_2 - 0.82 \times \text{P}_3 + 9.07 \times \text{P}_4 \quad (19)$$

$$\text{NO}_x = -22.78 + 1.68 \times \text{Temp} - 0.10 \times \text{RH} - 1.96 \times \text{WS} - 0.01 \times \text{WD} - 0.07 \times \text{AT} - 3.46 \times \text{P}_1 - 1.22 \times \text{P}_2 - 0.72 \times \text{P}_3 + 5.4 \times \text{P}_4 \quad (20)$$

$$\text{NO} = -14.12 + 0.53 \times \text{Temp} - 0.001 \times \text{RH} - 0.18 \times \text{WS} - 0.004 \times \text{WD} + 0.03 \times \text{AT} - 0.32 \times \text{P}_1 - 0.01 \times \text{P}_2 - 0.37 \times \text{P}_3 - 0.71 \times \text{P}_4 \quad (21)$$

$$\text{SO}_2 = 25.47 - 0.64 \times \text{Temp} - 0.05 \times \text{RH} - 0.72 \times \text{WS} - 0.01 \times \text{WD} + 0.36 \times \text{AT} - 0.11 \times \text{P}_1 - 0.74 \times \text{P}_2 - 1.09 \times \text{P}_3 + 1.94 \times \text{P}_4 \quad (22)$$

TABLE 2

Coefficient of determination R^2 for Sector-125,
located in Gautam Budh Nagar

	Meteorological data	Augmented data
PM _{2.5}	0.59	0.63
PM ₁₀	0.61	0.65
NO ₂	0.60	0.74
NO _x	0.59	0.73
NO	0.14	0.20
Ozone	0.64	0.86
SO ₂	0.59	0.59

$$\begin{aligned} \text{Ozone} = & -75.63 + 5.82 \times \text{Temp} - 0.97 \times \text{RH} \\ & + 1.34 \times \text{WS} + 0.08 \times \text{WD} - 0.19 \times \text{AT} \\ & - 8.34 \times P_1 - 4.51 \times P_2 + 12.45 \times P_3 + 0.4 \\ & \times P_4 \end{aligned} \quad (23)$$

Moreover, the model is evaluated with the Mean Absolute error (MAE) metric; the calculated errors are shown in Table 1 and the errors are found to be minimum for NO and maximum for PM₁₀. Due to the unavailability of meteorological data for stations Sector-62 and Knowledge Park-III, they are discarded from the analysis.

Compared to the regression based on meteorological data, the above regression with augmented data performs better in all the coefficient of determination R^2 estimates for all the pollutants. The higher value of R^2 shows the goodness of fit for the model. In Table 2. Coefficient of determination R^2 for Sector-125 located in Gautam Budh Nagar, the R^2 values for the model are compared with meteorological and augmented data for the station Sector-125. The model with only meteorological data explains the pollutants PM_{2.5} (59%), PM₁₀ (61%), NO₂ (60%), NO_x (59%), NO (14%), Ozone (64%), SO₂ (59%). In comparison, the model with augmented data explains PM_{2.5} (63%), PM₁₀ (65%), NO₂ (74%), NO_x (73%), NO (20%), Ozone (86%), and SO₂ (59%), the contrast suggests that with augmented data the model can explain more variability of pollution data. A similar observation is noticed for all the other stations, suggesting the importance of augmentation of meteorological data with binary lockdown variables.

5. Conclusion

The present study is conducted to thoroughly analyse pollutants PM_{2.5}, PM₁₀, NO₂, NO_x, NO, Ozone and SO₂ in Uttar Pradesh, India. The study timeline spans 2019 to 2021, including the infamous COVID-19 lockdown in 2020. To exhibit the effect of lockdown throughout the state with the help of IDW interpolation, only three phases, PL, P₁ and UL are chosen. According to the generated maps, all the pollutants, except Ozone and SO₂, show a significant decrease in P₁ as compared to PL and UL. Further, the phase-wise analysis for the year 2020 suggests a considerable amount of decrement in the pollution level for all the pollutants except Ozone and SO₂; the improvement in terms of percentage for pollutants are ranked as NO, NO_x, PM_{2.5}, NO₂, PM₁₀, Ozone and SO₂ from higher to lower.

In comparison with 2019, the pollution level in 2020 recorded a sharp decline in P₁-P₄ for all the pollutants except Ozone and SO₂ in a few instances. Moreover, the decrease or improvement in pollution levels is ranked as NO, NO_x, PM₁₀, NO₂, PM_{2.5}, SO₂ and Ozone from higher to lower. To analyse the spread of pollution data, standard deviation estimates are found to be lower in 2020 and relatively higher in 2019 and 2021. The pollution data are clustered more closely in 2020 than in 2019. To establish empirical relations between pollution levels and meteorological parameters and binary lockdown variables (P₁-P₄), the MLR model is used; the modelling results suggest that with the augmentation of (P₁-P₄), the overall power to explain the variation of pollution data has increased significantly, especially for NO_x, NO₂ and Ozone. In addition, satellite data is used for the phase-wise transitions for the aforementioned years; it implies that in 2020, a significant decrement in NO₂ and SO₂ levels are observed, while the Ozone level shows a low increment in some observations as well as a low decrement in other observations. Further, in the 2019-2020 transitions, the NO₂ level is significantly reduced, and the Ozone level is slightly increased, while SO₂ levels show no clear trend. In the 2020-2021 transition, a converse result is achieved except for SO₂. Furthermore, the correlation between ground and satellite data is estimated; it is found that the correlation for NO₂ is moderate to strong for four districts, while for Ozone and SO₂, only for one district.

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Abbreviations

The following abbreviations are used in this manuscript:

AT	Air Temperature
CPCB	Central Pollution Control Board
GEE	Google Earth Engine
IDW	Inverse Distance Weighted Interpolation
MLR	Multiple Linear Regression
NO	Nitrogen Monoxide
NO ₂	Nitrogen Dioxide
NO _x	Nitrogen oxides
P ₁ , P ₂ , P ₃ , P ₄	Binary Lockdown Variables
P ₁	Lockdown Phase-1
P ₂	Lockdown Phase-2
P ₃	Lockdown Phase-3
P ₄	Lockdown Phase-4
PL	Pre-lockdown Phase
PM ₁₀	Particulate matter having size ≤10 microns
PM _{2.5}	Particulate matter having size ≤2.5 microns
RH	Relative Humidity
SO ₂	Sulphur Dioxide
TROPOMI	Tropospheric Monitoring Instrument
UL	Unlock Phase
WS	Wind Speed

Disclaimer : The contents and views expressed in this study are the views of the authors and do not necessarily reflect the views of the organizations they belong to.

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