Temporal and Spatial Variations of Nitrogen Dioxide Concentrations in Kolkata, India

Aman Srivastava[1], Aditya Kumar Thakur[1], Abhishek Rai[1], Raj Narayan Yadava[2], Rahul Dev Garg[1], Pradeep Kumar Garg[1]

[1] Department of Civil Engineering, Indian Institute of Technology Roorkee, India - aman_s1@ce.iitr.ac.in; aditya_kt@ce.iitr.ac.in; abhishek_r@ce.iitr.ac.in; rdgarg@ce.iitr.ac.in; p.garg@ce.iitr.ac.in

[2] Department of Mining Engineering, Indian Institute of Technology (Indian School of Mines) Dhanbad, India – 23dr0130@iitism.ac.in

Keywords: Kolkata Pollution, Sentinel-5P, Spatiotemporal Analysis, Autocorrelation Analysis, Periodicity Assessment.

Abstract

Air pollution is a primary environmental concern in urban areas. This study examines the temporal and spatial variations in nitrogen dioxide (NO_2) concentrations in Kolkata from 2019 to 2023 using Sentinel-5P satellite data. The application of statistical techniques, including Global Moran's I and Fast Fourier Transform (FFT), highlights changes in NO_2 spatial distribution and identifies dominant periodicities. Yearly analysis reveals notable fluctuations in NO_2 levels, with a significant decline of approximately 9.1% between 2019 and 2020, attributed to reduced vehicular and industrial activities during the COVID-19 lockdown. However, by 2023, NO_2 concentrations had returned to pre-pandemic levels attributed to the resumption of economic activities. Spatial analysis reveals higher NO_2 concentrations in central built-up areas, including Ballygunge, Bhowanipore, and Park Street. At the same time, peripheral regions such as Metiabruz and Behala show lower levels, likely due to vegetated areas. Global Correspondence values indicate significant shifts in NO_2 distribution patterns over the study period. The pattern shifted during the COVID-19 pandemic but stabilized by 2023, aligning with pre-pandemic emission levels, but the monthly pattern was preserved. The FFT analysis reveals a dominant annual cycle with a frequency of 0.0833 cycles per month (12-month period) and an amplitude of 0.3520, along with a significant overall average component. Seasonal variations show higher concentrations in winter due to increased emissions and reduced levels in summer due to photolysis and monsoon rains. These findings underscore the importance of effective pollution management and continuous air quality monitoring to improve air quality in Kolkata.

1. Introduction

Air pollution has increasingly become one of the most severe environmental issues. The issue is more prominent, particularly in urban and industrial areas where population density, industrial activities, and vehicular emissions are concentrated. Further, nitrogen dioxide (NO_2) is a major pollutant that significantly impacts air quality and affects health. Prolonged exposure to high levels of NO_2 can play a role in asthma development and may heighten vulnerability to respiratory infections. This underscores the severity of NO_2 as a pollutant with substantial environmental and health impacts (Chauhan et al., 2003; Maltare and Vahora, 2023; Organization, 2021; Ravindra et al., 2016; Razavi-Termeh et al., 2021; Stanek et al., 2011). Numerous studies over the years have highlighted the increase in critical pollutants such as sulfur dioxide, nitrogen oxides, and particulate matter levels in India. The results consistently indicate significant health repercussions for populations exposed to these pollutants, particularly in high-risk urban and industrial areas. Studies also advocate for improved monitoring and regulatory steps to manage air quality for public health protection (Jion et al., 2023; Kaur and Pandey, 2021; Meo et al., 2022; Srivastava et al., 2025).

Kolkata, one of India’s largest and most densely populated cities, has been grappling with changes in NO_2 levels. It is mainly due to high industrial emissions, increasing traffic density, and policy interventions (Gupta et al., 2008; Karmakar, 2024). In addition to emission sources, meteorological factors play a substantial role in the variability of air quality in Kolkata. Seasonal changes in factors such as temperature, humidity, and precipitation are strongly correlated with fluctuations in pollutant concentrations, highlighting the dynamic nature of air pollution. These factors reveal strong correlations with various pollutants (Khan et al., 2023; Maltare et al., 2024). Further, industrial and vehicular activity was restricted to a greater extent during the COVID-19 pandemic. So, drastic changes in air pollutant distribution and air quality were observed during this period (Adam et al., 2021; Li et al., 2020). Beyond environmental and health impacts, pollution also affects social structures and dynamics. Many research studies explored the complex interactions between environmental changes and social dynamics to analyse how environmental changes influence community well-being and introduce social modifications (Entwisle, 2021; Fazey et al., 2021; Mishra and Thakur, 2023).

Previous studies on NO_2 distribution in Kolkata often overlooked the detailed spatiotemporal variations and patterns. Additionally, studies need to adequately address the impact of significant events, such as the COVID-19 lockdowns, on air quality changes. The spatial association of pollution and its seasonal pattern have also been unexplored. This study utilises Sentinel-5P satellite data to analyse the spatiotemporal variation of NO_2 in Kolkata from 2019 to 2023. The measures of various statistical parameters help understand the change over time, along with the distribution pattern of NO_2 over Kolkata. The study also examines spatial variability over the area by applying the quantile method for reclassification and calculating the value of Global Correspondence between the years. Further, the Fast Fourier Transform (FFT) algorithm was used to detect seasonal patterns (Musbah et al., 2020, 2019). Integrating all these results, the impact of the pandemic lockdown and subsequent economic recovery on NO_2 patterns was examined. Overall, the analysis offers insights into the effects of NO_2 and highlights the importance of effective pollution control measures in maintaining air quality.

2. Study Area

Kolkata, the largest urban agglomeration in eastern India, serves as the administrative capital of West Bengal and stands as a major cultural and economic centre. Situated along the banks of the Hooghly River, this historic city was known as a prominent port city nearly 300 years ago. Over the centuries, Kolkata has evolved from its colonial roots into a vibrant metropolis. It has a key role in the region's economy, culture, and politics (Bose, 2015; Gupta, 2023).

This contribution has been peer-reviewed. The double-blind peer-review was conducted on the basis of the full paper.
https://doi.org/10.5194/isprs-annals-X-G-2025-855-2025 | © Author(s) 2025. CC BY 4.0 License.

Its strategic location along the Hooghly River has been integral to its development, shaping its identity as a critical hub of trade and commerce in India (Yadav and Bhagat, 2015). The extensions of the study area are 22.4513°N to 22.6328°N and 88.2324°E to 88.4592°E, respectively, having an area of 196.3 sq. km. (Dasgupta et al., 2013). The major LULC classes in the city include built-up areas, which dominate most of the landscape, along with patches of vegetation, forest, waterbodies, and rangeland. These categories reflect the urbanized nature of the region with limited natural land cover (Figure 1). The upper part of Kolkata's sedimentary sequence features a 20-60 m thick layer of clay and silty clay, with groundwater occurring below in a confined condition (Sikdar et al., 1996). Integrated natural and anthropogenic factors make the city an important industrial centre and settlement, which contributes to the rising pollution in the city.

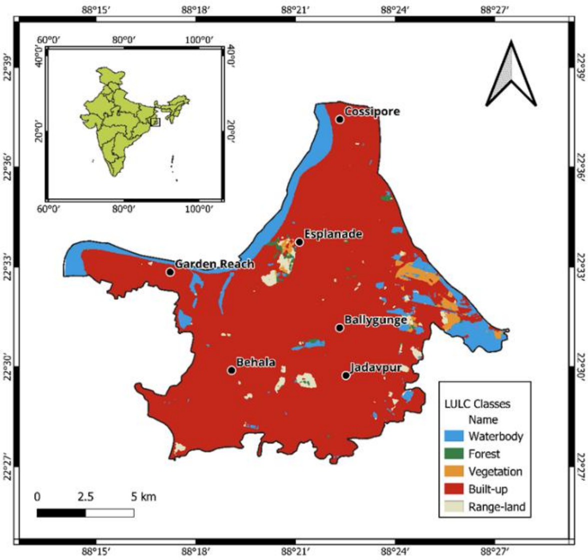


Figure 1. Study area map of Kolkata illustrating different LULC classes. Classification was done using Sentinel-2 data. Important locations within the city are also shown.

3. Methodology

3.1 Dataset

Several studies used the Sentinel dataset for multi-disaster assessment, including land surface deformation, land use land cover changes, pollution and flood detection, and other disaster monitoring (Alam et al., 2022; Bhattacharjee and Garg, 2024; Chowdhury and Dwarakish, 2022; Grimaldi et al., 2020; Jodhani et al., 2024; Mastro et al., 2022; Mishra and Jain, 2022; Mondal and Paul, 2023; Raju and Mehdi, 2023; Soni et al., 2025; Soudagar et al., 2025; Srivastava et al., 2025; Tang et al., 2024; Thakur et al., 2025a, 2025b, 2024; Verma and Vijay, 2024). This study utilises the Sentinel-5P satellite from the Copernicus program is effective in monitoring atmospheric composition. It can provide high-resolution global measurements of various atmospheric gases (Bodah et al., 2022; Савенець et al., 2019). This satellite is part of the European Space Agency's (ESA) Copernicus Earth observation program and is dedicated to monitoring air quality and atmospheric composition. It was launched in 2017 and uses the Tropospheric Monitoring Instrument (TROPOMI) to capture detailed air quality information. Its global coverage and daily observations make it useful for accessing trends of different pollutants.

3.2 Processing

The methodology for estimating NO_2 vertical column density involves several key steps shown in Figure 2. The measurement technique utilized is known as Differential Optical Absorption Spectroscopy (DOAS), which is based on the selective absorption of light by atmospheric trace gases (Anand et al., 2015; Chan et al., 2012; Platt et al., 2008). This method works on the distinct absorption features of NO_2 and O_3 in the visible spectrum, enabling their identification and quantification based on their unique spectral signatures. These features are utilized because each gas absorbs light at specific wavelengths, allowing for accurate differentiation and measurement through remote sensing techniques (Meena et al., 2003). Initially, Sentinel-5P satellite data is obtained from the TROPOMI sensor, which measures nitrogen dioxide (NO_2) along the satellite's viewing angle (slant path). The data undergoes pre-processing steps, including geolocation correction, cloud masking, and quality filtering to enhance accuracy. The slant column densities (SCDs) of NO_2 are then derived by analyzing the measured radiance. This is done by fitting the absorption features of NO_2 to the observed radiance spectrum, as described in Equation 1.

$$SCD = \int L.n(z)\, dz \qquad \text{…(Equation 1)}$$

L is the path length, and n(z) is the NO_2 number density as a function of altitude z. Further, the SCD is transformed to the vertical column density (VCD) using the air mass factor (Equation 2).

$$\boldsymbol{VCD = \frac{SCD}{AMF}} \qquad \text{…(Equation 2)}$$

Where AMF is the air mass factor, AMF is a dimensionless quantity that depends on factors such as observation geometry, atmospheric conditions etc.. This process involves the hyperspectral measurement. AMF corrects for the viewing geometry and atmospheric scattering (Dimitropoulou, 2021). Further resampling was done and map was created with specific resolution of 1km*1km. Finally, yearly statistical metrics—minimum, maximum, mean, and standard deviation—were calculated to assess temporal changes and spatial variability. A distribution map of NO_2 concentrations was overlaid on Kolkata's topographic map to identify high-concentration zones to identify pollution hotspots.

To evaluate NO_2 spatial distribution changes in Kolkata, NO_2 concentration maps for 2019–2023 were reclassified using the quantile method, creating equal-area classes ranging from very low to very high. The Global Moran's I formula (Equation 4) was applied to determine the spatial association between yearly maps. Pairwise Global Correspondence values were computed to assess the similarity between distribution patterns for consecutive years. Statistical shifts were interpreted in relation to economic and lockdown periods. Distribution maps were then overlaid on a topographic map to identify spatial patterns in NO_2 concentration across the city.

For monthly NO_2 analysis, data from 2019 to 2023 was collected, organized by month, and reshaped into a continuous time series. A moving average with a three-month window size smoothed out short-term variations, while cubic spline interpolation created a smooth trend curve through data points. The Fast Fourier Transform (FFT) was employed to detect dominant seasonal patterns and recurring periodic cycles in NO_2 concentration over time. By transforming the time-series data into the frequency domain, the FFT enabled the

https://doi.org/10.5194/isprs-annals-X-G-2025-855-2025 | © Author(s) 2025. CC BY 4.0 License.

identification of key frequency components and their corresponding amplitudes. This analysis provided insights into annual, sub-annual, etc. variations in NO_2 levels, revealing underlying temporal trends and cyclic behavior associated with anthropogenic activities and meteorological influences. Moreover, seasonal behaviour was interpreted by examining monthly variations, factoring in meteorological and socio-economic influences.

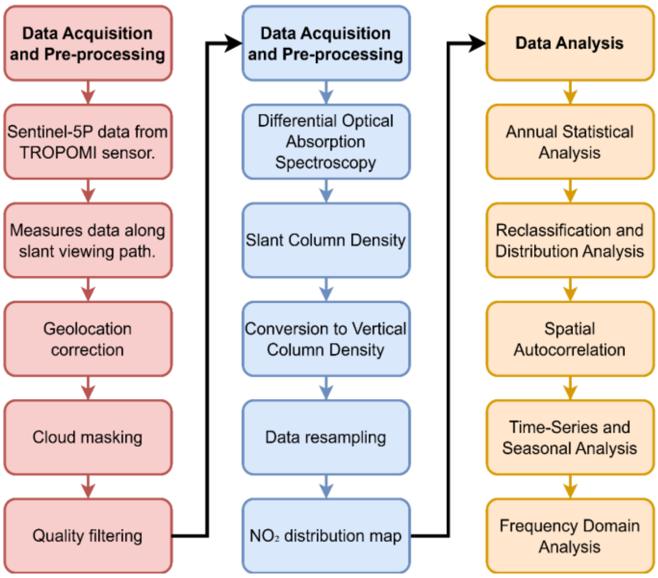


Figure 2. Methodological flowchart showing various steps involved in Sentinel 5P data retrieval along with different monthly and yearly analysis mechanisms.

4. Results and Discussions

4.1. General statistical analysis

Table 1. Spatial statistics of measured NO_2 for Kolkata for different years. Values are in $*10^{-4}$ mole/sq.m.

Year	Minimum	Maximum	Mean	Standard deviation
2019	1.1098	1.3639	1.2651	0.0627
2020	1.0287	1.2257	1.1493	0.0440
2021	1.1843	1.4507	1.3625	0.0634
2022	1.1163	1.3802	1.2820	0.0669
2023	1.2228	1.4356	1.3625	0.0479

Table 1 presents spatial statistics for analysing the variation in nitrogen dioxide (NO_2) concentrations in Kolkata from 2019 to 2023. Figure 3 depicts the distribution for different years. During the period of 2019 to 2023, NO_2 levels experienced noticeable fluctuations. A significant drop of approximately 9.1% is observed from 2019 to 2020. This decline was likely due to the reduced vehicular and industrial activities during the COVID-19 lockdown. Substantial reductions in both minimum and maximum values indicate a temporary improvement in air quality. However, NO_2 concentrations began to rise again in 2021, returning to pre-pandemic levels by 2023. The rebound can be attributed to the resumption of regular economic activities, increased industrial output, and a return to typical traffic patterns. By 2023, the mean NO_2 concentration was similar to that observed in 2021 and 2019, suggesting that air quality had reverted to its usual state as restrictions were lifted.

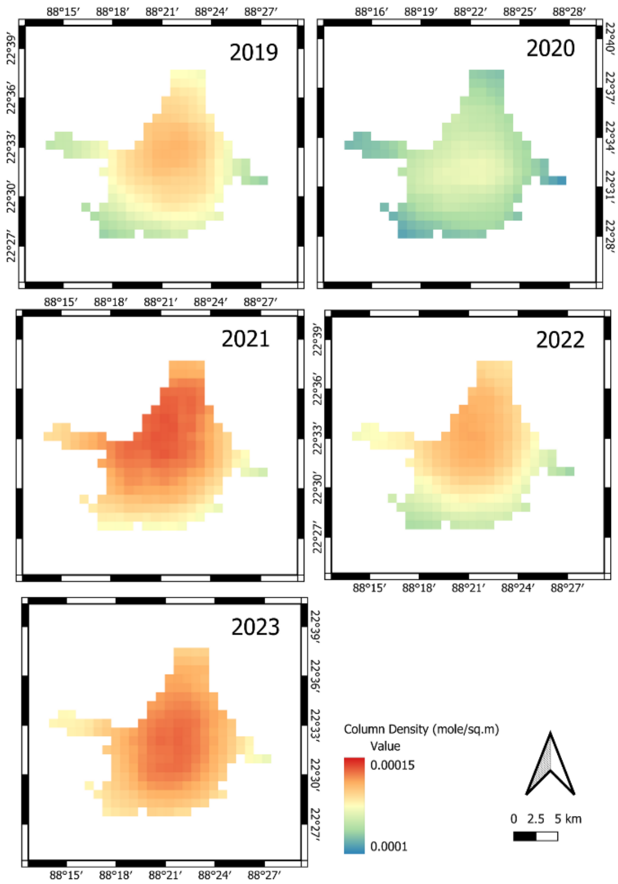


Figure 3. Yearly NO_2 column density distribution over Kolkata.

The standard deviation of NO_2 concentrations in Kolkata from 2019 to 2023 highlights fluctuations in spatial variability influenced by changes in human activities. The lowest deviation in 2020 corresponds to uniform NO_2 levels during the COVID-19 lockdown, while increased variability in 2022 reflects varied emission sources. By 2023, NO_2 distribution stabilized as pollution levels became more uniform across the city. Overlaying the distribution map of 2023 on a topographic map revealed specific areas within the city, such as Ballygunge, Bhowanipore, Taltala, Elgin, Park Street, Beniapukur, and Gariahat, with higher NO_2 concentrations. In contrast, peripheral areas like Metiabruz, Behala, and Garia showed lower levels, likely due to the presence of more vegetated regions. This data underscores the significant impact of human activities on air quality in Kolkata, highlighting both the temporary improvement during the lockdown and the challenges of sustaining lower pollution levels during the economic recovery, emphasizing the need for effective and ongoing pollution management strategies.

4.2. Correspondence analysis

Table 2 presents the Global Correspondence values between reclassified maps of NO_2 distribution over Kolkata from 2019 to 2023, calculated based on Global Moran's Index (Lee and Li, 2017; Mathur, 2015; Zhang et al., 2008). The maps were reclassified using the quantile method to ensure equal area representation for each class, as illustrated in Figure 4, and spatial autocorrelation was then assessed to evaluate overall clustering patterns across the years.

Table 2. Global measure of spatial association between different classes of NO_2 distribution over Kolkata.

Year	2019	2020	2021	2022
2020	0.3918			
2021	0.3914	0.2475		
2022	0.5016	0.2824	0.5653	
2023	0.4772	0.4744	0.2817	0.321

The values indicate the similarity of NO_2 spatial distribution between different years. The correspondence between 2019 and 2020 is 0.3918, suggesting a moderate shift in NO_2 patterns, likely due to COVID-19 lockdowns that significantly impacted traffic and industrial activities. The low correspondence of 0.2475 between 2020 and 2021 further supports the idea of substantial changes as activities resumed post-lockdown. A higher correspondence of 0.5653 between 2021 and 2022 indicates a return to more stable NO_2 distribution patterns as economic activities normalized. In 2023, the distribution showed moderate similarity to previous years, with values of 0.4772 compared to 2019 and 0.4744 compared to 2020, suggesting that NO_2 distribution patterns have stabilized, likely due to the combination of resumed economic activities and effective pollution control measures.

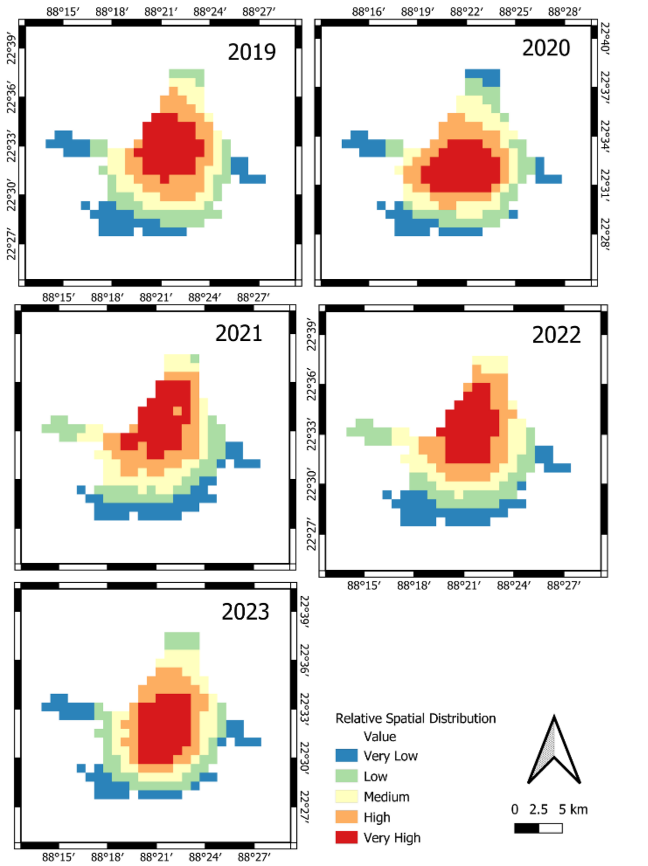


Figure 4. Yearly relative spatial distribution of NO2 over Kolkata.

4.3. Monthly Analysis

Table 3. Monthly Variation of NO_2 column density for different years. Values are in $*10^{-4}$ mole/sq.m.

Month	2019	2020	2021	2022	2023
January	1.70	1.57	1.58	1.68	1.56
February	1.75	1.60	1.93	1.91	1.70
March	1.59	1.12	1.74	1.37	1.51
April	1.20	1.06	1.25	1.11	1.60
May	1.10	0.98	1.14	1.15	1.39
June	1.26	0.98	1.21	1.05	1.33
July	0.99	0.92	0.97	0.79	0.86
August	0.95	0.88	1.02	0.99	1.07
September	0.93	0.92	1.05	1.03	0.91
October	1.10	0.98	1.35	1.10	1.40
November	1.28	1.14	1.43	1.43	1.46
December	1.31	1.57	1.42	1.73	1.48

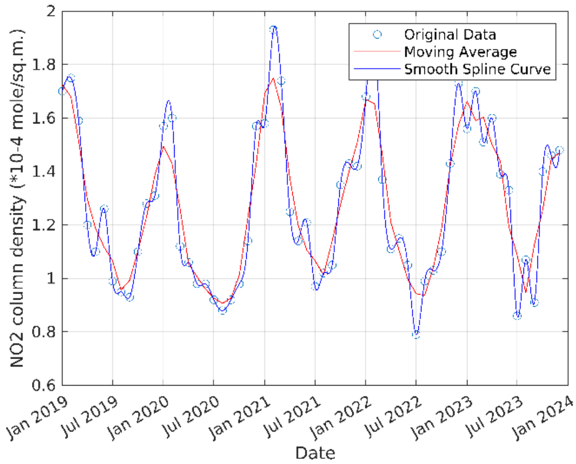


Figure 5. Continuous Time Series plot showing monthly variation of NO_2 for different years with Moving Average and Smooth Spline Curve.

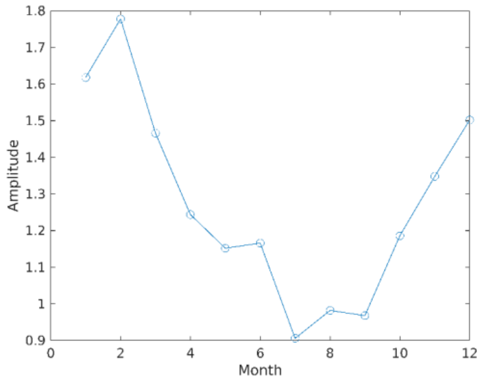
Table 3 displays Kolkata's monthly variation in NO_2 column density from 2019 to 2023 (Figure 5). The data, originally organized by year and month, is reshaped into a continuous time series to facilitate comprehensive analysis. The moving average technique with a window size of 3 months is applied to smooth out short-term fluctuations and highlight longer-term trends (Raudys et al., 2013). Additionally, a cubic spline interpolation was used to create a smooth curve through the data points (Sun et al., 2023). It estimates the unknown values between known data points by fitting a piecewise continuous curve. It provides a clearer representation of underlying patterns. Further, to analyze the seasonal behaviour of the time series data, a frequency domain conversion was applied using Fast Fourier Transform (FFT). The FFT was utilized to calculate the magnitude associated with each frequency component, aiding in the interpretation of the relative significance of various periodicities present in the NO_2 time series.

Table 4. Frequencies and Amplitudes obtained from FFT (Fast Fourier Transform)

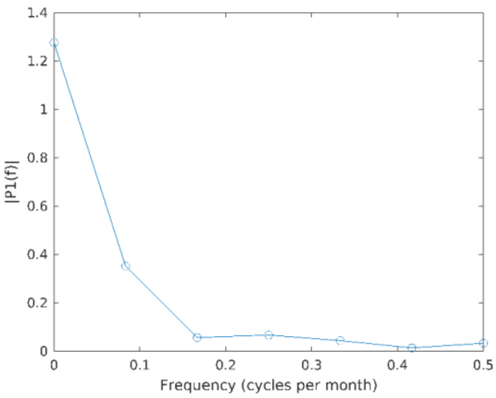
Frequency	Amplitude	Interpretation
0.0000	1.2763	This shows the overall average level of NO_2 concentration.
0.0833	0.3520	This indicates a yearly pattern—NO_2 levels tend to repeat or cycle every 12 months.

0.1667	0.0570	This shows a pattern that repeats every 6 months.
0.2500	0.0671	This represents changes that occur roughly every 4 months.
0.3333	0.0442	This reflects a repeating pattern every 3 months.
0.4167	0.0138	This shows smaller variations happening approximately every 2.4 months.
0.5000	0.0333	This indicates regular changes every 2 months.

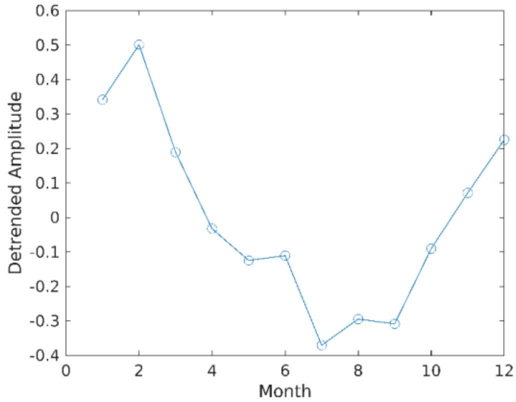
Table 4 summarizes the results of the FFT analysis. Figure 6 depicts the curves plotted for the results of FFT analysis. FFT reveals clear seasonal and annual trends. The FFT analysis revealed that the strongest component is at 0 cycles per month, corresponding to the overall average value of the dataset, with an amplitude of 1.2763. The next prominent frequency is 0.0833 cycles per month, which indicates a clear annual cycle (12-month periodicity), with an amplitude of 0.3520. This suggests that the data exhibits a strong yearly seasonality. Minor contributions from other frequencies, such as 0.1667 cycles per month (semi-annual cycle) and shorter-term cycles like 0.2500 (4-month cycle), were observed but with much lower amplitudes, indicating they play a smaller role in the data's behavior. The data shows a dominant annual cycle with weaker contributions from semi-annual and shorter periodicities.



(a)



(b)



(c)

Figure 6. Curve plotted for the results of FFT analysis: (a) Average Seasonal Data Across Years for different months; (b) Frequency domain of seasonal data with different amplitudes; (c) Average de-trended component of Data Across Years for different months.

During the winter months (November to February), NO_2 levels are generally higher. This increase is likely due to several factors: higher emissions from heating systems, increased vehicle emissions due to more prolonged engine warm-ups, and atmospheric conditions that reduce dispersion. During winter, temperature inversions are more common, trapping pollutants near the ground and leading to higher concentrations of NO_2 (Wallace et al., 2010; Wallace and Kanaroglou, 2009). Conversely, the summer months (April to September) show comparatively lower NO_2 levels. Higher temperatures during these months accelerate photolysis (Equation 5) and also enhance atmospheric dispersion (Gen et al., 2022; Goldberg et al., 2021).

$$NO_2 + h\nu \rightarrow NO + O \qquad \text{…(Equation 5)}$$

Where: hν represents the energy of a single photon of light, with h being Planck's constant and ν being the frequency of the UV light. O is an oxygen atom that can further react with molecular oxygen (O_2) to form ozone (O_3). As observed in many research studies, the increased rainfall associated with the monsoon season helps wash NO_2 out of the atmosphere; Kolkata also depicted a similar pattern (Choi et al., 2008; Loosmore and Cederwall, 2004). Additionally, lower heating emissions and changes in transportation patterns, such as reduced vehicular traffic during school vacations and summer holidays, contribute to the decline in NO_2 levels. A significant reduction in NO_2 levels was observed in 2020, particularly from March to June, correlating with the nationwide lockdown due to the COVID-19 pandemic, which led to reduced industrial activities, vehicular emissions, and overall human activity. This is evident in the sharp drop in March and April 2020 NO_2 levels compared to previous years. Post-2020, NO_2 levels gradually increase as economic activities resume, but they do not immediately return to pre-pandemic levels, indicating a phased recovery in emissions. For instance, February 2021 shows a notable rise compared to February 2020, reflecting increased industrial and vehicular activity as restrictions ease. This gradual increase highlights the lasting impact of the pandemic on air quality and the slow return to normalcy. The year-to-year variability in monthly NO_2 levels is influenced by changes in local emissions, meteorological conditions, and regulatory measures, such as stricter pollution controls and the promotion of cleaner technologies. The data underscores the importance of sustained efforts to manage air quality, especially in urban environments with dense populations and high levels of economic activity.

5. Conclusion

The analysis of NO_2 concentrations in Kolkata from 2019 to 2023 reveals a clear impact of human activities on air quality. The significant reduction in NO_2 levels during the 2020 COVID-19 lockdown highlights that significant air quality improvement can be achieved if emissions are strictly controlled. However, the concentration of NO_2 has increased after the resumption of economic activities. It highlights significant challenges in maintaining reduced pollution levels. The stabilization and re-rise of NO_2 levels by 2023 indicates a return to pre-pandemic air quality. This shows the need for sustainable efforts and effective pollution management strategies for long-term air quality improvement. The Correspondence values indicate a dynamic pattern in NO_2 distribution during the study period. This reflects the fluctuating nature of urban emissions and their response to varying levels of human activity. The central area, particularly, shows higher concentrations of NO_2 than the peripheral region, which may be attributed to vegetated areas. However, in 2021 and 2022, it has shifted towards northwest. Further, in recent years, moderate to high correspondence values have suggested stabilization phenomena. This may be attributed to balancing economic recovery, emissions and pollution control measures.

The analysis of NO_2 column density in Kolkata from 2019 to 2023 reveals significant seasonal and annual variations, with higher levels during winter due to increased emissions and atmospheric conditions that trap pollutants. Summer months show a reduction in NO_2 levels, driven by photolysis, better atmospheric dispersion, and monsoon rains. The FFT analysis reveals a dominant annual cycle with a prominent frequency of 0.0833 cycles per month (12-month period), an amplitude of 0.3520, and a notable overall average component at 0 cycles per month, with minor contributions from semi-annual and shorter-term cycles. The COVID-19 pandemic led to a sharp decline in NO_2 in 2020, with levels gradually rising post-lockdown, yet not fully returning to pre-pandemic levels, highlighting the long-term impacts of the pandemic and the importance of continued air quality management efforts. However, the need for ongoing monitoring and targeted interventions remains crucial. It can help achieve consistent and long-term improvements in air quality in urbanized cities like Kolkata.

Acknowledgement

The authors thank the Indian Institute of Technology Roorkee for providing the environment and facilities necessary for conducting this research work. We also extend our thanks to all those who contributed directly or indirectly to the successful completion of this work.

References

Adam, M.G., Tran, P.T.M., Balasubramanian, R., 2021. Air quality changes in cities during the COVID-19 lockdown: A critical review. Atmos. Res. 264, 105823.

Alam, M.S., Kumar, D., Chatterjee, R.S., 2022. Improving the capability of integrated DInSAR and PSI approach for better detection, monitoring, and analysis of land surface deformation in underground mining environment. Geocarto Int. 37, 3607–3641.

Anand, J.S., Monks, P.S., Leigh, R.J., 2015. An improved retrieval of tropospheric NO2 from space over polluted regions using an Earth radiance reference. Atmos. Meas. Tech. 8, 1519–1535. https://doi.org/10.5194/amt-8-1519-2015

Bhattacharjee, S., Garg, R.D., 2024. Estimation of sea ice drift and concentration during melt season using C-band dual-polarimetric Sentinel-1 data. Remote Sens. Appl. Soc. Environ. 33, 101104.

Bodah, B.W., Neckel, A., Maculan, L.S., Milanes, C.B., Korcelski, C., Ramírez, O., Mendez-Espinosa, J.F., Bodah, E.T., Oliveira, M.L.S., 2022. Sentinel-5P TROPOMI satellite application for NO2 and CO studies aiming at environmental valuation. J. Clean. Prod. 357, 131960.

Bose, P.S., 2015. Urban Development in India. Routledge. https://doi.org/10.4324/9781315745909

Chan, K.L., Pöhler, D., Kuhlmann, G., Hartl, A., Platt, U., Wenig, M.O., 2012. NO 2 measurements in Hong Kong using LED based long path differential optical absorption spectroscopy. Atmos. Meas. Tech. 5, 901–912.

Chauhan, A.J., Inskip, H.M., Linaker, C.H., Smith, S., Schreiber, J., Johnston, S.L., Holgate, S.T., 2003. Personal exposure to nitrogen dioxide (NO2) and the severity of virus-induced asthma in children. Lancet 361, 1939–1944.

Choi, Y.-S., Ho, C.-H., Kim, J., Gong, D.-Y., Park, R.J., 2008. The impact of aerosols on the summer rainfall frequency in China. J. Appl. Meteorol. Climatol. 47, 1802–1813.

Chowdhury, A., Dwarakish, G.S., 2022. Selection of algorithm for land use land cover classification and change detection. IJARSCT 2, 15–24.

Dasgupta, S., Gosain, A.K., Rao, S., Roy, S., Sarraf, M., 2013. A megacity in a changing climate: the case of Kolkata. Clim. Change 116, 747–766.

Dimitropoulou, E., 2021. Retrieval of the horizontal distributions of NO2, HCHO, and aerosols from urban MAX-DOAS measurements in support to air quality satellite validation.

Entwisle, B., 2021. Population responses to environmental change: looking back, looking forward. Popul. Environ. 42, 431–444.

Fazey, I., Carmen, E., Ross, H., Rao-Williams, J., Hodgson, A., Searle, B.A., AlWaer, H., Kenter, J.O., Knox, K., Butler, J.R.A., 2021. Social dynamics of community resilience building in the face of climate change: The case of three Scottish communities. Springer.

Gen, M., Liang, Z., Zhang, R., Mabato, B.R.G., Chan, C.K., 2022. Particulate nitrate photolysis in the atmosphere. Environ. Sci. Atmos. 2, 111–127.

Goldberg, D.L., Anenberg, S.C., Kerr, G.H., Mohegh, A., Lu, Z., Streets, D.G., 2021. TROPOMI NO2 in the United States: A detailed look at the annual averages, weekly cycles, effects of temperature, and correlation with surface NO2 concentrations. Earth's Futur. 9, e2020EF001665.

Grimaldi, S., Xu, J., Li, Y., Pauwels, V.R.N., Walker, J.P., 2020. Flood mapping under vegetation using single SAR acquisitions. Remote Sens. Environ. 237, 111582.

Gupta, A.K., Karar, K., Ayoob, S., John, K., 2008. Spatio-temporal characteristics of gaseous and particulate pollutants in an urban region of Kolkata, India. Atmos. Res. 87, 103–115.

Gupta, D., 2023. Evolution of an Indian City: From Calcutta to Kolkata. Int. J. Soc. Sci. Econ. Res. 8, 467–483.

Jion, M.M.M.F., Jannat, J.N., Mia, M.Y., Ali, M.A., Islam, M.S., Ibrahim, S.M., Pal, S.C., Islam, A., Sarker, A., Malafaia, G., Bilal, M., Islam, A.R.M.T., 2023. A critical review and prospect of NO2 and SO2 pollution over Asia: Hotspots, trends, and sources. Sci. Total Environ. 876. https://doi.org/10.1016/j.scitotenv.2023.162851

Jodhani, K.H., Gupta, N., Parmar, A.D., Bhavsar, J.D., Patel, H., Patel, D., Singh, S.K., Mishra, U., Omar, P. jee, 2024. Synergizing google earth engine and earth observations for potential impact of land use/ land cover on air quality. Results Eng. 22, 102039. https://doi.org/10.1016/j.rineng.2024.102039

Karmakar, J., 2024. Air Pollution and Particulate Matter in the Kolkata Metropolitan Area, India. J. Indian Assoc. Environ. Manag. 44, 52–59.

Kaur, R., Pandey, P., 2021. Air pollution, climate change, and human health in Indian cities: a brief review. Front. Sustain. Cities 3, 705131.

Khan, M., Tariq, S., Haq, Z.U., 2023. Variations in the aerosol index and its relationship with meteorological parameters over Pakistan using remote sensing. Environ. Sci. Pollut. Res. 30, 47913–47934.

Lee, J., Li, S., 2017. Extending Moran's index for measuring spatiotemporal clustering of geographic events. Geogr. Anal. 49, 36–57.

Li, L., Li, Q., Huang, L., Wang, Q., Zhu, A., Xu, J., Liu, Z., Li, H., Shi, L., Li, R., 2020. Air quality changes during the COVID-19 lockdown over the Yangtze River Delta Region: An insight into the impact of human activity pattern changes on air pollution variation. Sci. Total Environ. 732, 139282.

Loosmore, G.A., Cederwall, R.T., 2004. Precipitation scavenging of atmospheric aerosols for emergency response applications: testing an updated model with new real-time data. Atmos. Environ. 38, 993–1003.

Maltare, N.N., Vahora, S., 2023. Air Quality Index prediction using machine learning for Ahmedabad city. Digit. Chem. Eng. 7, 100093.

Maltare, N.N., Vahora, S., Jani, K., 2024. Seasonal analysis of meteorological parameters and air pollutant concentrations in Kolkata: An evaluation of their relationship. J. Clean. Prod. 436, 140514.

Mastro, P., Masiello, G., Serio, C., Pepe, A., 2022. Change Detection Techniques with Synthetic Aperture Radar Images: Experiments with Random Forests and Sentinel-1 Observations. Remote Sens. 14. https://doi.org/10.3390/rs14143323

Mathur, M., 2015. Spatial autocorrelation analysis in plant population: An overview. J. Appl. Nat. Sci. 7, 501.

Meena, G.S., Jadhav, D.B., Bhosale, C.S., 2003. Total column density variations of NO 2 and O 3 by automatic visible spectrometry over Pune, India. Curr. Sci. 171–179.

Meo, S.A., Alqahtani, S.A., AlRasheed, R.A., Aljedaie, G.M., Albarrak, R.M., 2022. Effect of environmental pollutants PM2. 5, CO, O3 and NO2, on the incidence and mortality of SARS-COV-2 in largest metropolitan cities, Delhi, Mumbai and Kolkata, India. J. King Saud Univ. 34, 101687.

Mishra, G.N., Thakur, A.K., 2023. Gateway of Sociological Thought. BFC Publications.

Mishra, V., Jain, K., 2022. Satellite based assessment of artificial reservoir induced landslides in data scarce environment: A case study of Baglihar reservoir in India. J. Appl. Geophys. 205, 104754.

Mondal, A., Paul, P.K., 2023. Monitoring of groundwater generated land subsidence by persistent scatterer analysis–A case study of the Kolkata Municipal Corporation (KMC), West Bengal. J. Earth Syst. Sci. 132, 181.

Musbah, H., Aly, H.H., Little, T.A., 2020. A novel approach for seasonality and trend detection using fast fourier transform in box-jenkins algorithm, in: 2020 IEEE Canadian Conference on Electrical and Computer Engineering (CCECE). IEEE, pp. 1–5.

Musbah, H., El-Hawary, M., Aly, H., 2019. Identifying seasonality in time series by applying fast fourier transform, in: 2019 IEEE Electrical Power and Energy Conference (EPEC). IEEE, pp. 1–4.

Organization, W.H., 2021. WHO global air quality guidelines: particulate matter (PM2. 5 and PM10), ozone, nitrogen dioxide, sulfur dioxide and carbon monoxide. World Health Organization.

Platt, U., Stutz, J., Platt, U., Stutz, J., 2008. Differential absorption spectroscopy. Springer.

Raju, A., Mehdi, K., 2023. SBAS-InSAR analysis of regional ground deformation accompanying coal fires in Jharia Coalfield, India. Geocarto Int. 38. https://doi.org/10.1080/10106049.2023.2167004

Raudys, A., Lenčiauskas, V., Malčius, E., 2013. Moving averages for financial data smoothing, in: Information and Software Technologies: 19th International Conference, ICIST 2013, Kaunas, Lithuania, October 2013. Proceedings 19. Springer, pp. 34–45.

Ravindra, K., Sidhu, M.K., Mor, S., John, S., Pyne, S., 2016. Air pollution in India: bridging the gap between science and policy. J. Hazardous, Toxic, Radioact. Waste 20, A4015003.

Razavi-Termeh, S.V., Sadeghi-Niaraki, A., Choi, S.-M., 2021. Effects of air pollution in Spatio-temporal modeling of asthma-prone areas using a machine learning model. Environ. Res. 200, 111344.

Sikdar, P.K., Biswas, A.B., Saha, A.K., 1996. A study on the possible land subsidence in Calcutta and Howrah cities due to groundwater overdraft. Indian J. Geol. 68, 193–200.

Soni, R., Alam, M.S., Vishwakarma, G.K., 2025. Prediction of InSAR deformation time-series using improved LSTM deep learning model. Sci. Rep. 15, 5333.

Soudagar, R., Chowdhury, A., Bhardwaj, A., 2025. Enhanced large-scale flood mapping using data-efficient unsupervised framework based on morphological active contour model and single synthetic aperture radar image. J. Environ. Manage. 380, 124836.

Srivastava, A., Thakur, A.K., Garg, R.D., 2025. An assessment of the spatiotemporal dynamics and seasonal trends in NO_2 concentrations across India using advanced statistical analysis. Remote Sens. Appl. Soc. Environ. 37, 101490. https://doi.org/10.1016/j.rsase.2025.101490

Stanek, L.W., Brown, J.S., Stanek, J., Gift, J., Costa, D.L., 2011. Air pollution toxicology—a brief review of the role of the science in shaping the current understanding of air pollution health risks. Toxicol. Sci. 120, S8–S27.

Sun, M., Lan, L., Zhu, C.-G., Lei, F., 2023. Cubic spline interpolation with optimal end conditions. J. Comput. Appl. Math. 425, 115039.

Tang, T., Zhang, L., Zhu, H., Ye, X., Fan, D., Li, X., Tong, H., Li, S., 2024. Quantifying Urban Daily Nitrogen Oxide Emissions from Satellite Observations. Atmosphere (Basel). 15, 1–12. https://doi.org/10.3390/atmos15040508

Thakur, A.K., Attri, L., Garg, R.D., Jain, K., Kumar, D., Chowdhury, A., 2024. Temporal and Spatial Dynamics of Subsidence in Eastern Jharia, India, in: ISPRS Annals of the Photogrammetry, Remote Sensing and Spatial Information Sciences. Copernicus Publications Göttingen, Germany, pp. 349–356. https://doi.org/https://doi.org/10.5194/isprs-annals-X-4-2024-349-2024

Thakur, A.K., Garg, R.D., Jain, K., 2025a. An assessment of different line-of-sight and ground velocity distributions for a comprehensive understanding of ground deformation patterns in East Jharia coalfield. Remote Sens. Appl. Soc. Environ. 37, 101446. https://doi.org/10.1016/j.rsase.2024.101446

Thakur, A.K., Garg, R.D., Jain, K., 2025b. Land subsidence dynamics and its structural impact assessment over East Jharia, Jharkhand, India. J. Earth Syst. Sci. 134, 114. https://doi.org/10.1007/s12040-025-02564-8

Verma, D., Vijay, S., 2024. Time-Series Analysis of Dam Deformation Using Satellite-Based InSAR Technique: Case Studies from Oroville, Pong, and Tehri Dams, in: IGARSS 2024-2024 IEEE International Geoscience and Remote Sensing Symposium. IEEE, pp. 11136–11140.

Wallace, J., Corr, D., Kanaroglou, P., 2010. Topographic and spatial impacts of temperature inversions on air quality using mobile air pollution surveys. Sci. Total Environ. 408, 5086–5096.

Wallace, J., Kanaroglou, P., 2009. The effect of temperature inversions on ground-level nitrogen dioxide (NO2) and fine particulate matter (PM2. 5) using temperature profiles from the Atmospheric Infrared Sounder (AIRS). Sci. Total Environ. 407, 5085–5095.

Yadav, V., Bhagat, R.B., 2015. Spatial dynamics of population in Kolkata urban agglomeration. Urban Dev. challenges, risks Resil. asian mega cities 157–173.

Zhang, C., Luo, L., Xu, W., Ledwith, V., 2008. Use of local Moran’s I and GIS to identify pollution hotspots of Pb in urban soils of Galway, Ireland. Sci. Total Environ. 398, 212–221.

Савенець, М.В., Дворецька, І.В., Надточій, Л.М., 2019. Current state of atmospheric air pollution in Ukraine based on Sentinel-5P satellite data. Visnyk VN Karazin Kharkiv Natl. Univ. Ser. Geol. Geogr. Ecol. 221–233.