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Research Paper

Lockdown during COVID-19 pandemic: A case study from Indian cities shows insignificant effects on persistent property of urban air quality

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Abstract

The influence of reduction in emissions on the inherent temporal characteristics of PM$_{2.5}$ and NO$_2$ concentration time series in six urban cities of India is assessed by computing the Hurst exponent using Detrended Fluctuation Analysis (DFA) during the lockdown period (March 24–April 20, 2020) and the corresponding period during the previous two years (i.e., 2018 and 2019). The analysis suggests the anticipated impact of confinement on the PM$_{2.5}$ and NO$_2$ concentration in urban cities, causing low concentrations. It is observed that the original PM$_{2.5}$ and NO$_2$ concentration time series is persistent but filtering the time series by fitting the autoregressive process of order 1 on the actual time series and subtracting it changes the persistence property significantly. It indicates the presence of linear correlations in the PM$_{2.5}$ and NO$_2$ concentrations. Hurst exponent of the PM$_{2.5}$ and NO$_2$ concentration during the lockdown period and previous two years shows that the inherent temporal characteristics of the short-term air pollutant concentrations (APCs) time series do not change even after withholding the emissions. The meteorological variations also do not change over the three time periods. The finding helps in developing the prediction models for future policy decisions to improve urban air quality across cities.

1. Introduction

Extended memory property has been observed as the distinctive characteristics of air pollutant concentration (APC) time series. Chelani (2016a), in a review paper, and others (Varotsos et al., 2005; Lee et al., 2006; Shi et al., 2015) observed the presence of persistence in APCs over a period of time up to a specific limit. APCs such as PM$_{2.5}$ (Particulate matter of size <2.5 $\mu$m) and NO$_2$ (Nitrogen dioxide) have detrimental health effects. PM$_{2.5}$ can travel deeply into the respiratory tract and can cause coughing, allergy, asthma, painful breathing, chronic bronchitis, decreased lung functions, and heart disease (WHO, 2013; Gollakota et al., 2021). The presence of statistical persistence in the time series of APCs suggests the uniformity in the generation of APCs. Persistence property is linked to long memory, and self-organizing criticality (SOC) of APCs in many published articles (Shi and Liu, 2009; Shi et al., 2015; Chelani, 2016a). Self-organizing criticality in APCs has been interpreted in conjunction with the atmosphere’s removal mechanism leading to self-cleansing of APCs (Shi and Liu, 2009; Montzka et al., 2011; Chelani, 2013; Shi et al., 2015). The phenomena of accumulation and dispersion of APCs over time are linked with the presence of persistence property by Meraz et al. (2015). The time series with the patterns that have a correlation with the past patterns can be termed as the persistent time series, which can also be called the time series with long-range correlations (Chelani, 2016b). The intrinsic evolution of the system and the presence of external factors such as meteorology and anthropogenic emissions govern the persistence in the time series.

In the above studies, the temporal characteristics in terms of persistence property were studied in the time series of APCs, which usually have an increasing or insignificant trend due to anthropogenic activities. Although various technological and policy-based interventions have been introduced in the past to reduce the emissions, significant reduction has not been observed in APCs. The persistence property has not been evaluated for APC time...
series with a sudden change. It is of interest to assess the influence of the sudden change or reduction in air quality on its persistent property.

With the onset of the COVID-19 pandemic, several countries imposed complete or partial lockdowns to prevent its spread (Ambade et al., 2020; Gautam and Hens, 2020; Gautam and Trivedi, 2020; Ambade et al., 2021). COVID-19 is an infectious, deadly disease declared as a pandemic by the World Health Organization. It is caused by contact with respiratory droplets exhaled by the infected person. Physical distancing is one of the preferable ways to reduce the spread of the virus. Due to this, measures like complete or partial lockdown have been adopted in several countries to flatten the infection curve by social and physical distancing (Ranjan et al., 2020). The measures such as shutting down of schools and cinema halls, malls, shops, and small-scale industries dealing with non-essential items, and other activities involving mass gatherings, e.g., restriction on the number of people attending funerals and weddings, etc., have been imposed in several countries. Only essential services were usually retained, i.e., groceries, shops, vegetable vendors that too with social distancing. The complete lockdown was initiated in India from March 24, 2020 to April 20, 2020 (Gautam, 2020a; Mahato et al., 2020; Ranjan et al., 2020). With the essential services, few power plants were also allowed to function, considering them as vital services.

Several sources of PM$_{2.5}$ and NO$_2$ pollution such as traffic, industries and combustion related activities were brought to a minimum during the lockdown period. The lockdown, albeit, has been putting excessive pressure on the economy of the nations, it has nevertheless proven a boon from the environmental perspective. Water and air pollution levels have significantly dropped in various regions (Arora et al., 2020; Gautam, 2020b; Gautam et al., 2020; Bera et al., 2021). Air pollution levels have reduced considerably in multiple cities worldwide due to the marginal anthropogenic activities during the lockdown (Lian et al., 2020; Mahato et al., 2020; Ottmani et al., 2020; Patel et al., 2020; Sharma et al., 2020; Sicard et al., 2020; Siciliano et al., 2020; Gautam et al., 2021a; Shi et al., 2021; Yuan et al., 2021). Ozone levels, however, have been observed to be increasing along with a decrease in NO$_2$, NO, and PM$_{2.5}$ levels in most cities (Sicard et al., 2020; Siciliano et al., 2020). In the studies carried out in various cities globally on the influence of lockdowns on APCs changes, emission reduction was the major driving factor causing the reduction in APCs (Chen et al., 2020; Patel et al., 2020; Shi and Braseur, 2020; Shi et al., 2021; Yuan et al., 2021). In a study conducted by Shi et al. (2021) in 11 cities located in different geographical regions with varying climates on the impact of lockdown on deseasonalized air pollutant concentrations, a more minor than expected influence was observed. It was suggested that although the observed concentration seemed to have changed significantly but the analysis after detrending and deseasonalizing of the time series showed the much lesser influence of lockdown.

In Indian cities, with minimal traffic flow during the lockdown, a decrease in air pollution was reported in several newspapers (CNN, 2020). An improvement in air quality during the lockdown period due to limited activities encourages to initiation of related measures during the periods of high air pollution in the area. In a study by GBD (2019), air pollution has been termed as the 4th risk factor for deaths globally. Studying the influence of no-activity or limited-activity on APCs provides a way to reduce the number of related deaths. The change in the concentration of air pollutants has therefore been studied rigorously during the lockdown period. The natural experiment on emission source reductions, as pointed out in Patel et al. (2020) provides a unique opportunity to study the influence of change in APCs on the temporal characteristics of APC time series. In a study on the effect of lockdown on change in APCs, Sicard et al. (2020) urged the need to study the air pollution formation mechanism and spatiotemporal patterns during the lockdown. Understanding the temporal characteristics of APCs in terms of their persistence is essential for developing the prediction models which utilize the property of scale invariance of the data. Very few studies have focused on this aspect of studying the influence of lockdown on the temporal characteristics of air pollution time series. In a study by Cameletti (2000), interrupted time series analysis with lockdown period helped in understanding the temporal variations in the APCs time series. The persistence property was, however, not evaluated. The induced lockdown might have altered the well-established persistence property of APCs. It has, however, not been attempted to investigate the difference in the inherent characteristics of the time series of air pollutant concentrations (APCs) with the reduction in the concentration. More specifically, as far as known to the authors, no such study has been performed to assess whether the significant reduction in the concentrations of air pollutants may have resulted in the change in the persistence property of APCs. A study is, therefore, initiated to assess the temporal behavior of the APCs time series during and before the lockdown period. There are many techniques to study the persistence in the time series including, rescaled-range analysis, detrended fluctuation analysis (DFA), autocorrelation function, spectral analysis, etc. DFA has outperformed other techniques in many studies, even for non-stationary time series (Shi and Liu, 2009; Chelani, 2013), and can be used in the time series with the presence of trends (Varotsos et al., 2005; Shi and Liu, 2009). In this study, Hurst exponent using DFA is computed for PM$_{2.5}$ and NO$_2$ concentration observed over six major cities of India. The persistence is studied for the lockdown period in 2020, i.e., March 24, 2020–April 20. The persistence property in APCs during a similar period in 2018 and 2019 is also studied to compare with the low activity period. The inferences drawn from the study can be useful to policymakers in taking appropriate decisions to manage the air pollution in an area.

2. Study area and data used

Central and State Pollution Control Boards in India operate Continuous Ambient Air Quality Monitoring Stations (CAAAQMS) in major cities. In each city, CAAQSMS is being conducted at one or more locations. The data is provided online with a frequency of 1 h and 24 h. PM$_{2.5}$ and NO$_2$ concentration at six cities, including three metros (Delhi, Kolkata, and Chennai), two urban cities with ongoing development activities (Hyderabad and Nagpur), and a city with a super thermal power station (Chandrapur) are selected for the study (CPCB, 2020). The inclusion of the city with a power plant that was not shut down during the lockdown would enable the analysis of its effect on the location's air quality. The location of the cities is given in Fig. 1. Though the data is provided for many ambient air quality parameters such as PM$_{2.5}$, NO$_2$, SO$_2$, and Ozone, only PM$_{2.5}$ and NO$_2$ are used in the study as SO$_2$ concentration is usually low and does not depict any trend. The concentration is more or less the same throughout the year. PM$_{2.5}$ and NO$_2$ concentrations are primary pollutants. The study on ozone which is a secondary pollutant shall be carried out and reported somewhere else. The strict lockdown has been initiated in India from March 24, 2020, to April 20, 2020. Therefore, the period is considered to study its influence on air pollution in PM$_{2.5}$ and NO$_2$ concentrations. The corresponding period in 2018 and 2019 is considered for comparison purposes. The missing values were found to range from 1% to 31% in the entire data set. These values were imputed by fitting a linear model separately on the PM$_{2.5}$ and NO$_2$ data during different years in R4.0.0 (R Development Core Team, 2010).
3. Methodology

Detrended Fluctuation Analysis (DFA) is used to detect the presence of persistence in the time series (Peng et al., 1993). For this, the APC time series $y$ with length $N$ and mean $\bar{y}$ is first integrated using Eq. (1).

$$z(k) = \sum_{i=1}^{k} [y(i) - \bar{y}]$$

(1)

where $\tau$ is the time lag, $k = 1, 2, \ldots, N$. The integrated time series $z(k)$, is divided into non-overlapping segments of equal sizes as $n$. The local detrending is then performed by fitting the least-squares line to each segment. For this, the $y$-coordinate denoted by $Z_n(k)$ of the straight line is used to detrend the time series $z(k)$ as $z(k) - Z_n(k)$ in each segment. The detrended fluctuation function or the root mean squares fluctuation, $F(n)$ over segment length, $n$ is calculated as:

$$F(n) = \sqrt{\frac{1}{N} \sum_{k=1}^{n} [z(k) - Z_n(k)]^2}$$

(2)

where $N$ is the number of observations. Usually, fluctuation function $F(n)$ increases with segment size $n$ (Peng et al., 1994). The linear relationship between $F(n)$ and $n$ suggests the presence of scaling in the time series. The root mean square fluctuation function $F(n)$ is shown to be proportional to segment length $n$ as $F(n) \sim n^\alpha$ with the scaling exponent $\alpha$ (Peng et al., 1995; Zhu and Liu, 2003). To obtain the scaling exponent $\alpha$, root mean squares fluctuation function, $F(n)$ is typically plotted over segment length, $n$ on a log–log scale. The straight line is fitted to the curve of $F(n)$ vs $n$ on the log–log plot. The slope is computed for the straight line, which represents the scaling exponent $\alpha$. The value of the scaling exponent $\alpha$ defines the characteristics or temporal property of the time series. For the time series with $\alpha$ lying between 0.5 and 1.0, the presence of long-range power-law correlations i.e., persistence, is indicated. In the time series with $\alpha$ lying between 0 and 0.5, anti-persistence or power-law anti-correlations are present. In contrast, for the time series with $\alpha = 0.5$, it suggests that the time series is uncorrelated (Peng et al., 2002). Even sometimes, $\alpha$ ranges between 1 and 1.5, indicating the stronger long-range correlations in the time series.

The flow of the computations is given below:

1. Integrate the time series using Eq. (1);
2. Divide the integrated time series into different segments of length $n$;
3. Locally detrend the time series over segments using the respective slope;
4. Calculate the fluctuation function, $F(n)$ for different segments lengths, $n$;
(5) Obtain log–log plot of $F(n)$ over $n$;
(6) Obtain slope of the straight line fitted to log–log plot of $F(n)$.
The slope represents the scaling exponent $\alpha$ over $n$.

To assess the presence of persistence, the above computations are performed for PM$_{2.5}$ and NO$_2$ concentration time series observed during March 24–April 20 for three years as 2018, 2019, and 2020 separately.

4. Results and discussions

Fig. 2 shows the box plot of 1 h PM$_{2.5}$ and NO$_2$ concentration observed in six cities during March 24–April 20 in 2018, 2019, and 2020. The standard threshold of 60 $\mu$g m$^{-3}$ for 24 h frequency of sampling for PM$_{2.5}$ stipulated by the Central Pollution Control Board (CPCB), New Delhi is exceeded significantly in Delhi by about 64%, 55%, and 22% in 2018, 2019, and 2020, respectively. The standards are not available by CPCB for 1 h frequency for PM$_{2.5}$ and NO$_2$ concentration, the comparison is therefore carried out with the available 24 h standards. At Nagpur and Chandrapur, the % of exceedance to PM$_{2.5}$ average is about 20%–30% in 2018 and 2019. In 2020, PM$_{2.5}$ concentration exceedance is observed to be <5% in all the cities except Delhi. High PM$_{2.5}$ concentration in Delhi is due to several factors such as traffic emissions, power plants, and intrusion of dust from the neighboring areas. NO$_2$ concentration exceeded the CPCB standard of 80 $\mu$g m$^{-3}$ in 2019 by about 22%, 6%, and 9% in Delhi, Kolkata, and Nagpur. In 2018, the NO$_2$ standard was exceeded by about 15% and 10% in Hyderabad and Nagpur. In 2020, NO$_2$ concentration exceedance to CPCB standard is <3% in all the cities. Delhi is observed to be the most polluted among the
selected cities in terms of PM$_{2.5}$ and NO$_2$ concentration, and PM$_{2.5}$ concentration has exceeded more as compared to NO$_2$ concentration.

While comparing the concentration observed during the lockdown period with the average concentration for the corresponding period during the previous two years, it is observed that PM$_{2.5}$ concentration has decreased during the lockdown period by 47% in Delhi, 25% in Kolkata, 30% in Hyderabad, 58% in Chennai, 51% in Nagpur and 30% in Chandrapur, respectively. NO$_2$ concentration has decreased in 2020 by 57% in Delhi and Kolkata, 12% in Hyderabad, 91% in Chennai, 49% in Nagpur, and 16% in Chandrapur. The analysis suggests the significant influence of lockdown on PM$_{2.5}$ and NO$_2$ concentration in most of the cities.

For comparison, diurnal variations in PM$_{2.5}$ and NO$_2$ concentration over three years in all the cities are plotted in Fig. 3a–f. PM$_{2.5}$ concentration has reduced in 2020 as compared to the corresponding period in 2018 and 2019 in all the cities except in Kolkata. In Chennai, PM$_{2.5}$ concentration is observed to be high in 2020 as compared to 2019 during the night hours. The diurnal variations in PM$_{2.5}$ concentration are similar in Delhi, Hyderabad, Nagpur, and Chandrapur with bimodal behavior (Fig. 3a–f). Pollutant concentration starts building up in the morning from 6 to 10 h and decreases during the afternoon to evening. Another built-up in the concentration is seen from 20.00 to 23.00 h in the night. Due to anthropogenic activities during the morning hours, PM$_{2.5}$ concentration is high in many areas. Lower concentration during the daytime is attributed to high temperature and wind velocity conditions increasing boundary layer height (Zhao et al., 2009). Dilution of APCs caused by higher boundary layer height leads to a reduction in APCs. The bimodal behavior in diurnal PM$_{2.5}$ concentration
is more pronounced in Delhi as compared to other cities. The diurnal variations are less noticeable in Chennai and Kolkata. The fewer variations in daily behavior suggest the ongoing anthropogenic activities throughout the day in these cities.

Diurnal variations in NO$_2$ concentrations show high concentrations during morning and night hours. The bimodal behavior is observed in NO$_2$ concentration in all the cities with a smaller peak in morning hours and a higher peak in night hours. In Chennai, Chandrapur, and Hyderabad, the diurnal variations were not observed in 2020. The influence of lockdown on NO$_2$ concentration is visible in these cities. NO$_2$ concentration is found to be associated with traffic emissions in urban areas (Zhao et al., 2009). Low traffic volume during the lockdown may have resulted in less diurnal variations in NO$_2$ concentrations.

Further, DFA is carried out to assess the influence of lockdown on the persistence property of the pollutant concentration time series. For this, the time series is integrated over the segment sizes in the range 10:200 with the increment of size 10 to ensure the detailed time scaling using Eq. (1). To compute the fluctuation function $F(n)$ over the different segment sizes, $n$ based on Eq. (2), R4.0.0 is used. $F(n)$ is then plotted over segment size, $n$ on the log-log scale in Fig. 4a–f for PM$_{2.5}$ and Fig. 5a–f for NO$_2$ concentration, respectively. The straight line is then fitted to the curve of log $F(n)$ vs log $n$. The Hurst exponent or scaling exponent, $\alpha$ is computed as the slope of the fitted straight line. The Hurst exponent is calculated for the three time periods i.e. during 2018, 2019, and 2020 for March 24–April 20, and is given in Table 1. The original PM$_{2.5}$ time series shows that the scaling exponent, $\alpha > 0.7$ and for NO$_2$ concentration, $\alpha > 0.6$ in all the cities. This indicates persistence in the time series of PM$_{2.5}$ and NO$_2$ concentrations during 2018, 2019, and 2020 for the selected cities. However, it has been suggested that the presence of linear correlations in the time series may influence the computation of scaling exponent, which tends to be on the higher side and causing false interpretation of persistence property (Hu et al., 2001; Chelani, 2016b). The differencing or removing the first-order correlation by auto-regressing at lag 1 i.e. applying an autoregressive model of order 1 (AR1) and performing the computations on the AR1 filtered time series, can precisely represent the underlying persistence in the time series. The scaling exponent is therefore computed also on the AR1 filtered time series. It can be seen from Table 1 that for AR1 filtered PM$_{2.5}$ concentration, $\alpha > 0.6$ during 2018 and <0.55 during 2019 and 2020 in Delhi. For Kolkata, Hyderabad, Chennai, Nagpur, and Chandrapur, PM$_{2.5}$ possesses the anti-persistence property during the three years. For AR1 filtered NO$_2$ concentration, $\alpha$ is observed to be <0.55 during the three years in all the cities. The time series

![Fig. 4. DFA of PM$_{2.5}$ concentration during lockdown and corresponding period in 2018 and 2019 in a) Delhi. b) Kolkata. c) Hyderabad. d) Chennai. e) Nagpur. f) Chandrapur.](image-url)
continues to possess similar characteristics during the lockdown period like previous years. For PM$_{2.5}$ concentration at Delhi, however, a decline in the persistence property is observed. In the studies carried out on the persistence in the APCs time series, Gil-Alana et al. (2020) studied the persistence in particulate matter in 50 US states and found that 8 states have a high level of persistence, no persistence in 2 states, and anti-persistence in the remaining states. In a similar study, Liu et al. (2015) characterized the tempo-

![Fig. 5. DFA of NO$_2$ concentration during lockdown and corresponding period in 2018 and 2019 in a) Delhi. b) Kolkata. c) Hyderabad. d) Chennai. e) Nagpur. f) Chandrapur.]

| City     | Original Time Series | AR Filtered Time Series |
|----------|----------------------|-------------------------|
|          | 2018 | 2019 | 2020 | 2018 | 2019 | 2020 | 2018 | 2019 | 2020 | 2018 | 2019 | 2020 |
| PM$_{2.5}$ Delhi | 0.836 | 0.804 | 0.718 | 0.590 | 0.560 | 0.507 |
| Kolkata  | 0.984 | 1.068 | 0.823 | 0.366 | 0.401 | 0.290 |
| Hyderabad | 0.829 | 0.990 | 0.962 | 0.292 | 0.449 | 0.415 |
| Chennai  | 0.897 | 1.046 | 0.878 | 0.328 | 0.472 | 0.476 |
| Nagpur   | 0.823 | 0.985 | 0.806 | 0.430 | 0.486 | 0.387 |
| Chandrapur | 0.830 | 0.881 | 0.913 | 0.348 | 0.376 | 0.489 |
| NO$_2$ Delhi | 1.072 | 0.894 | 0.753 | 0.344 | 0.367 | 0.336 |
| Kolkata  | 0.829 | 0.905 | 0.887 | 0.470 | 0.389 | 0.545 |
| Hyderabad | 0.655 | 0.635 | 1.152 | 0.341 | 0.328 | 0.391 |
| Chennai  | 0.850 | 0.659 | 0.824 | 0.473 | 0.474 | 0.443 |
| Nagpur   | 0.671 | 0.659 | 1.113 | 0.318 | 0.277 | 0.512 |
| Chandrapur | 0.625 | 0.841 | 1.197 | 0.268 | 0.353 | 0.519 |
rual fluctuations of SO2, NO2, PM10, and air pollution indices in Shanghai and observed different dynamical characters of the time series at different time scales. Windsor and Toumi (2001) observed high persistence up to 400 days in ozone levels. Varotsos et al. (2005) and Weng et al. (2008) observed persistence in the deseasonalized time series of ozone concentration. In other studies, the persistence or anti-persistence was observed in APCs time series (Zhu and Liu, 2003; Varotsos et al., 2006; Varotsos and Kirk-Davidoff, 2006; Shi et al., 2008; Chelani, 2009; Lau et al., 2009; Yuval and Broday, 2010; Perez et al., 2011).

The above analysis suggests that the inherent temporal characteristics of the time series (anti-persistence), in general, remain the same in 2020 compared to the behavior of the time series in 2018 and 2019 leading to the interpretation that the temporal correlations have not been distorted, despite of withholding the emission activities. Further, the reduction in the value of the scaling exponent of AR1 filtered time series as compared to the original one indicates the presence of linear temporal correlations and their influence on the estimation of the value of $\alpha$. The presence of linear temporal correlations in the time series of PM2.5 and NO2 concentration can be interpreted as; the values in close temporal proximity with one another are correlated at short time legs (Box et al., 1994). Long-range correlations on the other hand can be interpreted as the presence of correlation in all the values at long time lags. The anti-persistence in the AR1 filtered time series of PM2.5 and NO2 concentration during the lockdown period and the corresponding period during 2018 and 2019 suggests the non-random behavior of the time series. It also reveals the dependence of the observed concentration on the previous observations in addition to the influence of other factors. Anti-persistence indicates that the decrease in historical concentration influences the increase in today’s concentration and vice versa (Chelani, 2013; Chelani, 2016a). Air pollutants are generated due to several factors such as emission sources, geography, weather patterns, and climatic

![Pollution rose diagram of PM2.5 concentration in lockdown period in 2020 and corresponding period in 2018 and 2019 for a) Delhi. b) Kolkata. c) Hyderabad. d) Chennai. e) Nagpur. f) Chandrapur.](image-url)
The temporal evolution of pollutant concentrations is dependent on the current and past state of these factors. The persistence in the time series suggests the temporal dependence and uniformity in the generation mechanism over time (Chelani, 2016b). Despite the reduction in PM$_{2.5}$ and NO$_2$ concentration is observed during the confinement period, the inherent temporal characteristics of the APCs time series do not change. The process of accumulation and dispersion of APCs over a period of time helps in understanding the presence of long- or short-range correlations in the time series. Meteorological phenomena affect APCs in the long term and anthropogenic emissions possess cyclical patterns and have a short-term influence on the APCs (Meraz et al., 2015; Gautam et al., 2020; Gautam et al., 2021b). The presence of linear correlations in the original APCs time series and anti-persistence in the AR1 filtered time series suggests the influence of both factors.

It may, however, be noted that the results are restricted to a short period as the analysis is carried out only for the duration of confinement i.e., approximately one month. The similar temporal characteristics during the detention and normal period may indicate the similarity in meteorological conditions in three time periods. The pollution roses are plotted to analyze for any variations in PM$_{2.5}$ and NO$_2$ concentration in the three time periods. It can be seen from Figs. 6a and 7a that in Delhi, PM$_{2.5}$ and NO$_2$ are predominantly from the North-West direction in 2018 and 2019 with a
A moderate contribution from the South-East direction in 2018. West followed by North–West direction is primarily associated with PM$_{2.5}$ concentration in 2020. In Kolkata (Figs. 6b and 7b), PM$_{2.5}$ $> 35$ $\mu g$ m$^{-3}$ and NO$_2$ $> 20$ $\mu g$ m$^{-3}$ are observed to be from South–South–West (SSW) and South–West direction in 2018 and 2019. On the other hand, the predominant direction is the same in 2020 but the associated concentration is quite reduced due to fewer activities. In Hyderabad (Figs. 6c and 7c), PM$_{2.5}$ and NO$_2$ concentrations are observed to be associated predominantly with wind direction from the East-West sector in 2018 and the South-East sector in 2019 and 2020. In Chennai (Figs. 6d and 7d), PM$_{2.5}$ $> 40$ $\mu g$ m$^{-3}$ and NO$_2$ $> 20$ $\mu g$ m$^{-3}$ are observed from South-East direction in 2018 and PM$_{2.5}$ $> 40$ $\mu g$ m$^{-3}$ from South-West direction in 2019. South-East direction prevailed in 2020. In Nagpur (Figs. 6e and 7e), the South-West to South-East sector predominantly contributes PM$_{2.5}$ in the range 30–180 $\mu g$ m$^{-3}$ in 2018 and 2019; and 10–60 $\mu g$ m$^{-3}$ in 2020. East-West sector is predominant for high NO$_2$ contribution. In Chandrapur (Figs. 6f and 7f), during 2018 and 2019, high PM$_{2.5}$ and NO$_2$ is observed to be associated with the East-West sector with predominant South and South-South-West (SSW) direction. In 2020, SSW and South-West direction were prevailing. In general, the prevailing wind direction had not much changed in 2020, but due to lower emissions, the concentration has reduced in the particular dominant order in all the cities. The reduction in concentration due to lower emissions is observed in many cities (Patel et al., 2020; Shi and Brasseur, 2020; Yuan et al., 2021). The finding of similar temporal characteristics in the three time periods is supported by the insignificant changes in the meteorological variables in the lockdown period and the corresponding period during previous years. The information on the invariance of persistence property in PM$_{2.5}$ and NO$_2$ concentration even after withdrawing the emissions is useful while developing the prediction models of APCs. Future policy decisions to improve the air quality across the cities can rely on APCs’ inherent and intact temporal property.

![Pollution rose diagram of NO$_2$ concentration in lockdown period in 2020 and corresponding period in 2018 and 2019 for a) Delhi. b) Kolkata. c) Hyderabad. d) Chennai. e) Nagpur. f) Chandrapur.](image-url)
5. Conclusions

The influence of reduction in emissions on the persistence property of PM$_{2.5}$ and NO$_2$ concentration in six urban cities of India is assessed by analyzing the time series observed during the lockdown period and corresponding period during the previous two years. PM$_{2.5}$ concentration has been observed to be decreased during the lockdown period by 25%–58% in all the cities compared to the average concentration during 2018–2019. NO$_2$ concentration is observed to be reduced in 2020 by 12%–91% as compared to the average concentration in 2018–2019 in all the cities. The analysis suggests the influence of lockdown on the PM$_{2.5}$ and NO$_2$ concentration observed during the short time period in most of the cities. The study of persistence property in PM$_{2.5}$ and NO$_2$ concentration during the lockdown period and the similar time period during the previous two years using DFA reveals the persistence in the original time series and anti-persistence in AR1 filtered time series. The implementation of lockdown and thereby reducing the emissions does not impact the temporal characteristics in terms of the persistence property of PM$_{2.5}$ and NO$_2$ concentration. Further, the variations in meteorological parameters also remain similar during the lockdown and in the corresponding period in previous years. The finding is helpful while developing the prediction models of APCs. Future policy decisions to improve the air quality across the cities can rely on APCs‘ inherent and intact temporal property even after the reduction in emissions.

Declaration of Competing Interest

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

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