# Importance of meteorology and chemistry in determining air pollutant levels during COVID-19 lockdown in Indian cities

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## Abstract

Indian cities can experience severe air pollution, and the reduction in activity during the COVID-19 lockdown offered a natural experiment to study the contribution of local sources. The current work aimed to quantify the changes due to the lockdown in $NO_X$, $O_3$ and $PM_{2.5}$ in two contrasting cities in India (Delhi and Hyderabad) using a boosted regression tree model to account for the influence of meteorology. The median $NO_X$ and $PM_{2.5}$ concentrations were observed to decrease after lockdown in both cities, up to 57% and 75% for $PM_{2.5}$ and NOx, respectively when compared to previous years. After normalization due to meteorology the calculated reduction after lockdown for $PM_{2.5}$ was small (<8%) in both cities, and was likely less attributable to changes local emissions, but rather due changes in background levels (i.e. regional source(s)). The reduction of NOx due to lockdown varied by site (on average 5-30%), likely reflecting differences in relative proximity of local sources to the monitoring site, demonstrating the key influence of meteorology on ambient levels post-lockdown. Ozone was observed to increase after lockdown at both sites in Delhi, likely due to changes in relative amounts of precursor concentrations promoting ozone production, suggesting a volatile organic compound (VOC)-limited regime in Delhi. Thus, the calculated reduction in air pollutants due to lockdown in the current work cannot be extrapolated to be solely from a reduction in emissions and instead reflects the overall change in ambient levels, as meteorology and atmospheric chemical process also contributed.

**Environmental Significance Statement**

To accurately quantify impact of short-term interventions (such as COVID-19 lockdown) on air pollutant levels, meteorology and atmospheric chemistry need to be considered in addition to emission changes. We demonstrate that regional sources have a significant influence on $PM_{2.5}$ levels in Delhi and Hyderabad due to the small reduction calculated post-lockdown after weather-normalization, indicating that future $PM_{2.5}$ mitigation strategies should focus on national-scale, as well as local sources. Furthermore, we demonstrate with field measurements that ozone production in Delhi is likely volatile organic compound (VOC)-limited, in agreement with previous modelling predictions, indicating that ozone mitigation should focus on dominant VOC sources. This work highlights the complexity in developing mitigation strategies for air pollution due to its non-linear relationships with emissions, chemistry and meteorology.

# 1.0 Introduction

Exposure to air pollution is a well-established public health risk, with $PM_{2.5}$ (defined as airborne particles with an aerodynamic diameter less than 2.5 um) of particular concern [1]. India experiences some of the worst air pollution globally [2], with nine Indian cities among the top ten most polluted cities in the world for air pollution, as reported by the World Health Organization in 2016 [3]. Of most concern across India is ambient particle pollution, with the four largest cities in India (Delhi, Chennai, Hyderabad and Mumbai) having population-weighted annual-mean $PM_{2.5}$ concentrations (72 $\mu g\ m^{-3}$) almost double Indian regulatory limits [4]. As a result, India has a disproportionally high mortality and disease burden due to air pollution, with Balakrishnan et al.[5] estimating that air pollution exposure, specifically $PM_{2.5}$, resulted in 1.27 million deaths across India in 2017, with the burden higher in the northern states. With $PM_{2.5}$ levels across India forecast to rise owing in part to increased urbanization, the disease burden due to air pollution exposure is expected to worsen [6].

Like many countries, to mitigate the spread of COVID-19 through social distancing, India implemented a nationwide lockdown, restricting citizens' activities and movements as well as the closures of non-essential businesses and workplaces. The resultant reduction in major urban sources such as traffic, industry and construction activity would lead to decreased emissions, and hence potentially improvements in air quality. Therefore, the COVID-19 lockdown acts a natural experiment to study the contribution of local sources of air pollutants in cities for an extended period under normal meteorological conditions. Consequently, there is a fast-growing number of studies that have aimed to quantify the reduction in air pollutants during lockdown, with Kumar et al.[7] and Kroll et al.[8] providing a summary of recent work. Overall, the consensus within the literature is that levels of air pollution have typically decreased after the implementation of lockdown globally (See e.g. [9–12]). Recent work in China demonstrated reductions of up to 90% in emissions, primarily from vehicles and manufacturing, during lockdown but also unexpectedly $PM_{2.5}$ mass concentrations across Northern China [13]. Le and co-authors proposed that unusually high humidity led to increased secondary aerosol formation, which combined with stagnant air patterns, led to severe haze events, highlighting the non-linear nature of atmospheric chemistry as well as the importance of meteorology.

Owing to its severe air pollution, there have been a number of studies already published analyzing the effect of lockdown on air quality in India and, overall, notable reductions after lockdown have been reported across the country [7,14,15]. Pathakoti et al. [16] estimated using satellite data that, compared to 5-year mean levels, aerosol and $NO_2$ levels decreased by 24% and 17%, respectively. The effect of lockdown on air quality varied across India, with reported reductions in $PM_{2.5}$ of 19-43%, 41-53%, 26-54%, 23-36% and 10-30% for Chennai, Delhi, Hyderabad, Kolkata and Mumbai, respectively, with the level of reduction seemingly related to traffic volume [7]. For $NO_2$, similar levels of reductions after lockdown have been reported across Indian cities, with one study estimating it ranged between 50-70% for these cities [17]. However, much of this work in India has been observationally based, that is comparing measurements before and after the implementation of lockdown to determine the change in observed levels (e.g.[7,17]). The implicit assumption of this approach is that observed changes are driven exclusively by changing emissions, yet meteorology and atmospheric chemistry play a significant role in determining ambient pollutant levels [8]. When assessing changes in air pollutants due to short-term interventions (such as lockdown), these two factors need to be considered, with previous work demonstrating the importance of accounting for changes in meteorology [11,13,15,18,19].

The current work aims to quantify the changes in regulated air pollutants levels (i.e. NOx, $O_3$ and $PM_{2.5}$) due to the lockdown in two contrasting cities in India. We used two methods to achieve this aim, firstly we simply compared observed concentrations during the lockdown period to the corresponding dates in the last three years. Secondly, we employed a boosted regression tree (BRT) model to predict concentrations post-lockdown and compared these predicted values to the measured concentrations, in order to account for the effect of meteorology on pollutant levels. Therefore, we primarily focus on normalizing the effect of meteorology on observed levels in order to estimate change in levels after lockdown. The results of these two approaches to quantify the change in air pollutant levels due to lockdown are compared to explore the importance of meteorology. Finally, the changes in pollutant levels after lockdown allowed us to explore the chemical regime for local $O_3$ production in Delhi.

# 2.0 Method

## 2.1 Description of study sites

We chose Delhi and Hyderabad for this study, as they are both large inland cities but located in the north and south of India, respectively. Delhi is the largest city in India and experiences the highest levels of air pollution[4]. This is partly due to Delhi being located on the Indo-Gangetic plain, which experiences significant regional air pollution due to seasonal agricultural burning [20]. Hyderabad is the fourth largest city in India and is outside the regional air pollution that affects much of northern India. Consequently, Hyderabad experiences typically lower levels of $PM_{2.5}$ compared to Delhi; however severe pollution events are common in Hyderabad [4].

## 2.2 Data analysis

The data used in the study was obtained from the publicly available database on the Central Pollution Control board (CPCB) of India website (https://cpcb.nic.in/), using data collected by the CPCB, Delhi Pollution Control Committee (DPCC), Haryana State Pollution Control Board (HSPCB) and Telangana State Pollution Control Board (TSPCB). As the national lockdown was introduced on 23 March 2020, we collected hourly data between 1 March 2017 and 24 April 2020 for the following species: $PM_{2.5}$, NOx, $NO_2$, NO, and $O_3$. The lockdown across India did not end on 24 April, but we have chosen to focus on the initial month after its implementation (known as phase-I) as this period encompasses the most severe restrictions on citizens' activity [7]. We focused on urban background sites and these were chosen primarily based upon data availability for the above dates, with 2 sites selected in Delhi: RK Puram (28.563212, 77.186954) and ITO (928.628527, 77.240851). For Hyderabad, 2 sites were selected: Zoo Park (17.349707, 78.451440) and Santhanagar (17.455925, 78.433330). All collected data underwent quality control checks prior to analysis as recommended in Pant et al.[21]. All data processing was performed in R (v3.6.2) primarily utilizing the openair package [22]. Hourly meteorological and visibility data for 2017-2020 was obtained for Safdarjung (Delhi) and Begumpet (Hyderabad) airports as these were closest to the monitoring sites of interest using the worldmet package in R.

## 2.3 BRT model description

To predict pollutant concentrations based on meteorology, a boosted regression tree (BRT) model was developed using the deweather package in R. We chose to focus on $PM_{2.5}$ and NOx as these have direct emission sources in urban areas. To build the BRT model at each site we followed the procedure outlined in Carslaw et al.[19] and we used meteorological data, measured and background concentrations of the pollutant of interest along with time-based co-variates (e.g. time of day, day of week).

Meteorological measurements were obtained from the two airport sites, which included relative humidity, atmospheric pressure, dew point, wind speed, wind direction and temperature.

Background levels were included as previous work has shown this can significantly improve the predicting power of the BRT model [19,23]. The background sites were selected to be upwind of the sites of interest, based on the prevailing wind direction (NW at both cities) as well as data availability over the time period required. Only one site was suitable for Hyderabad (ICRISAT Patancheru), as there were few sites to the NW, and therefore the measurements from this site were taken as representative of background levels. In comparison, at Delhi five background sites were available upwind with enough data coverage and included Vikas Sadan, Gurugram, Alipur, Bawana and Najafargh. The median of the measured concentration at five sites were used as the background concentrations for the model, to limit any local sources emissions overly affecting the analysis.

While BRT models are typically robust against including too many variables, in order to minimize the associated error in the predictions, there is typically an optimum number of co-variates. Therefore, we built a series of test models using a multi-year dataset of the parameters above (2016-2020) by systematically changing the number of co-variates to determine the optimal suite. The optimal model was chosen based on its predictive capability (using a randomly selected 25% of the dataset). An advantage of the BRT approach is that the model outputs are physically and chemically meaningful and can be explored by partial dependencies of the co-variates, which is the relationship between the pollutant of interest and the covariates used in the model. To further aid the selection of the optimal model, we examined the model partial dependences to ensure if they made chemical or physical sense, for example if NOx decreased with increasing wind speed as would be expected if local emissions dominate.

The optimized BRT model was used to independently predict pollutant concentrations based only on the meteorology, for 2 months pre-lockdown (1 Feb to 22 Mar 2020) and for 1-month during phase-I lockdown (23 Mar to 23 Apr 2020). In order to optimize the predictive power for each model, the number of iterations/trees were set independently to equate the number of data points. This approach minimizes the variance of the model and improves the prediction capability of the concentrations of pollutants, based on the chosen co-variates using a randomized approach [24,25]. We built separate BRT models for $PM_{2.5}$ and NOx for each site in Delhi and Hyderabad, because the source influence would be expected to vary (e.g. the direction of important sources relative to the site). Owing to poor data coverage post-lockdown, we did not employ this analysis for NOx at Zoo Park and $PM_{2.5}$ at Santhanagar. For NOx and $PM_{2.5}$ at all sites, the background concentration and temporal trends were the most important co-variates for the model, followed by meteorology; dew point, air temperature, wind speed, RH and wind direction. The partial dependencies of each meteorological co-variate differed between the two cities and for NOx and $PM_{2.5}$, as would be expected. The optimized BRT model for $PM_{2.5}$ at both sites in Delhi (RK Puram and ITO), were found to have similar co-variate influence. This was likely due to strong influence of background concentrations on the BRT models at both sites, and this is discussed later in the manuscript. For NOx, the BRT models were notably different in terms of co-variate influence at RK Puram and ITO.

# 3.0 Results and Discussion

## 3.1 Time series of pollutants pre- and post-lockdown

Fig 1 presents a time series of selected species levels ($PM_{2.5}$, NOx and $O_3$) for March and April 2020 at RK Puram, Delhi and Zoo Park, Hyderabad. The corresponding time series for other sites are presented in Figs S1 and S2, Supporting Information. In India, a nationwide lockdown came into force on the 23 March 2020 and a clear and rapid decrease in NOx was observed after this date at all sites (Figs 1, S1 and S2). As NOx is a primary pollutant (i.e. directly emitted into the atmosphere from primarily anthropogenic sources such as vehicles), this reduction would be expected if there was significant reduction in human activity during lockdown and is consistent with studies elsewhere [10,11].

Contrasting trends in $PM_{2.5}$ and ozone after lockdown were observed at Delhi and Hyderabad (Fig 1). At Hyderabad, the levels of $PM_{2.5}$ and ozone were not observed to change after lockdown (23 March, Fig 1), as would be expected if regional sources were dominant for these two species. At the two Delhi sites, there is an apparent reduction in the levels of $PM_{2.5}$ immediately after lockdown compared to the before (Fig 1), with levels appearing to recover towards pre-lockdown levels after 2 weeks (i.e. on the 6th April). While this may point to a reduction in primary emissions for $PM_{2.5}$, a significant rain event that coincided with the implementation of lockdown, may also explain these observed changes. Therefore, this would suggest that meteorology influenced the observed levels during the lockdown period.

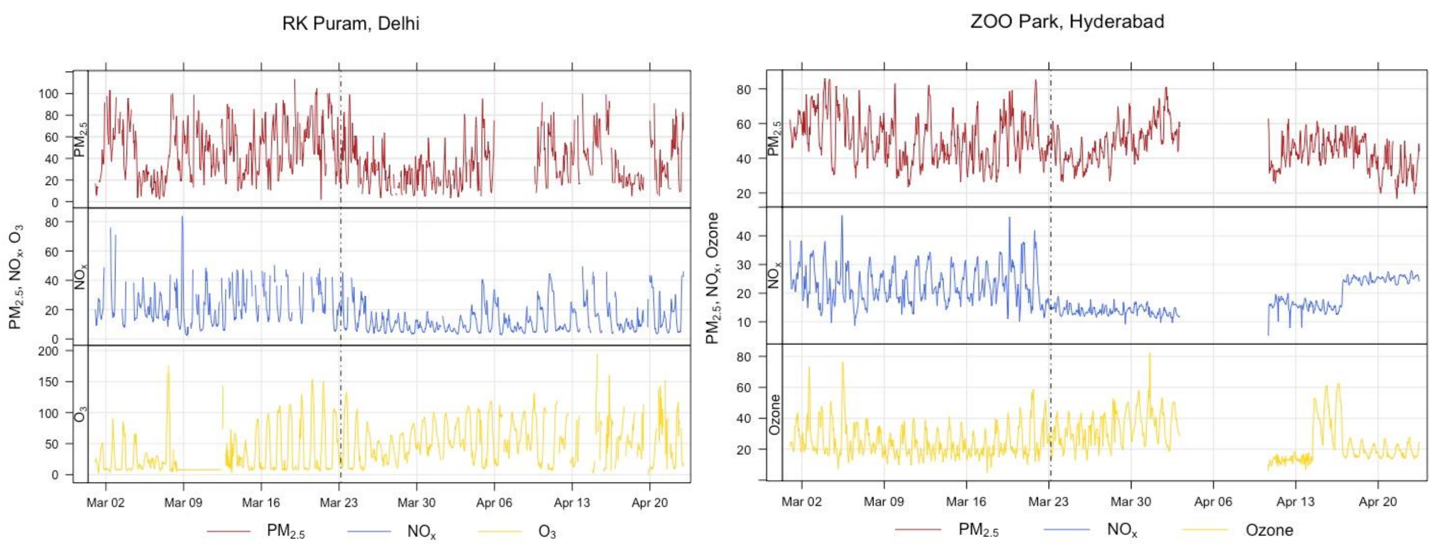


Fig 1: A time series of $PM_{2.5}$ (μg/m$^3$), NOx (ppbv) and $O_3$ (μg/m$^3$) levels pre-lockdown and during phase-I lockdown at RK Puram, Delhi and Zoo Park, Hyderabad. The marker placed on 23 March denotes the start of phase-I lockdown.

## 3.2 Comparison of concentrations during lockdown period to previous years

We first compared the levels of $PM_{2.5}$, NOx and $O_3$ during the phase-I lockdown period (24 March to 24 April 2020) to the corresponding dates in previous three years (24 March to 24 April 2017-2019, referred to as L3Y) to evaluate the changes due to lockdown. This comparison is shown in Figs 2 and 3 for $PM_{2.5}$ and NOx, respectively. Generally, the median levels during phase-I lockdown were lower than the L3Y in both cities (Table 1). Overall, we observed a greater reduction in median NOx compared to $PM_{2.5}$ levels at each site (Table 1). The exception was ITO, where the median NOx levels were comparable during phase-I lockdown compared to L3Y (Fig 3), while at the other sites the reduction in median NOx levels ranged from 34-75%. From Fig 3, the inter-quartile ranges were notably different at most sites, suggesting the observed reduction during phase-I lockdown was significant and likely reflects that NOx has more local emissions sources affected by the lockdown (e.g., vehicle emissions).

The largest change for $PM_{2.5}$ during phase-I lockdown compared to L3Y was observed at RK Puram, where the median $PM_{2.5}$ mass concentration decreased by 57%. The reduction in $PM_{2.5}$ during phase-I lockdown was similar at the other sites (11-36%, Table 1), and is lower than previously reported. Sharma et al.[15] reported a decrease of 34% in mean $PM_{2.5}$ mass concentrations across North India during lockdown compared to previous years, while Kumar et al[7] calculated a decrease of 41-53% and 26-54% for Delhi and Hyderabad, respectively. The differences in calculated reduction between studies may reflect differences in lockdown time periods chosen for analysis, as well as monitoring site locations within the cities. However, while the median levels for both $PM_{2.5}$ were lower during phase-I lockdown compared to L3Y, we observed similar inter-quartile ranges (Fig 2) for most sites (with exception of RK Puram), suggesting the changes may not be significant. This suggests that regional sources of $PM_{2.5}$ may be dominant at both cities, and that meteorology needs to be considered in order to properly account for regional source influence. Understanding changes in regional or background levels is critical to properly assess changes in local emissions, and in the next section we employed a BRT model to predict the influence of meteorology on $PM_{2.5}$ and NOx levels during phase-I lockdown.

Table 1: Median levels of $PM_{2.5}$ and NOx during the phase-I lockdown period (24 March – 24 April 2020) and corresponding dates for 2017-19 (L3Y).

| | | | *$PM_{2.5}$ ($\mu g\ m^{-3}$)* | | *NOx (ppbv)* | |
|---|---|---|---|---|---|---|
| *Delhi* | | | 2020 | L3Y | 2020 | L3Y |
| | RK Puram | Median | 36.3 | 83.3 | 14.9 | 60.6 |
| | | % decrease in phase-I | 57% | | 75% | |
| | ITO | Median | 63.0 | 73.0 | 51.2 | 49.3 |
| | | % decrease in phase-I | 14% | | -4% | |
| *Hyderabad* | Zoo park | Median | 47.0 | 52.8 | 18.2 | 34.1 |
| | | % decrease in phase-I | 11% | | 47% | |
| | Santhanagar | Median | 35.3 | 49.5 | 9.8 | 28.4 |
| | | % decrease in phase-I | 29% | | 66% | |

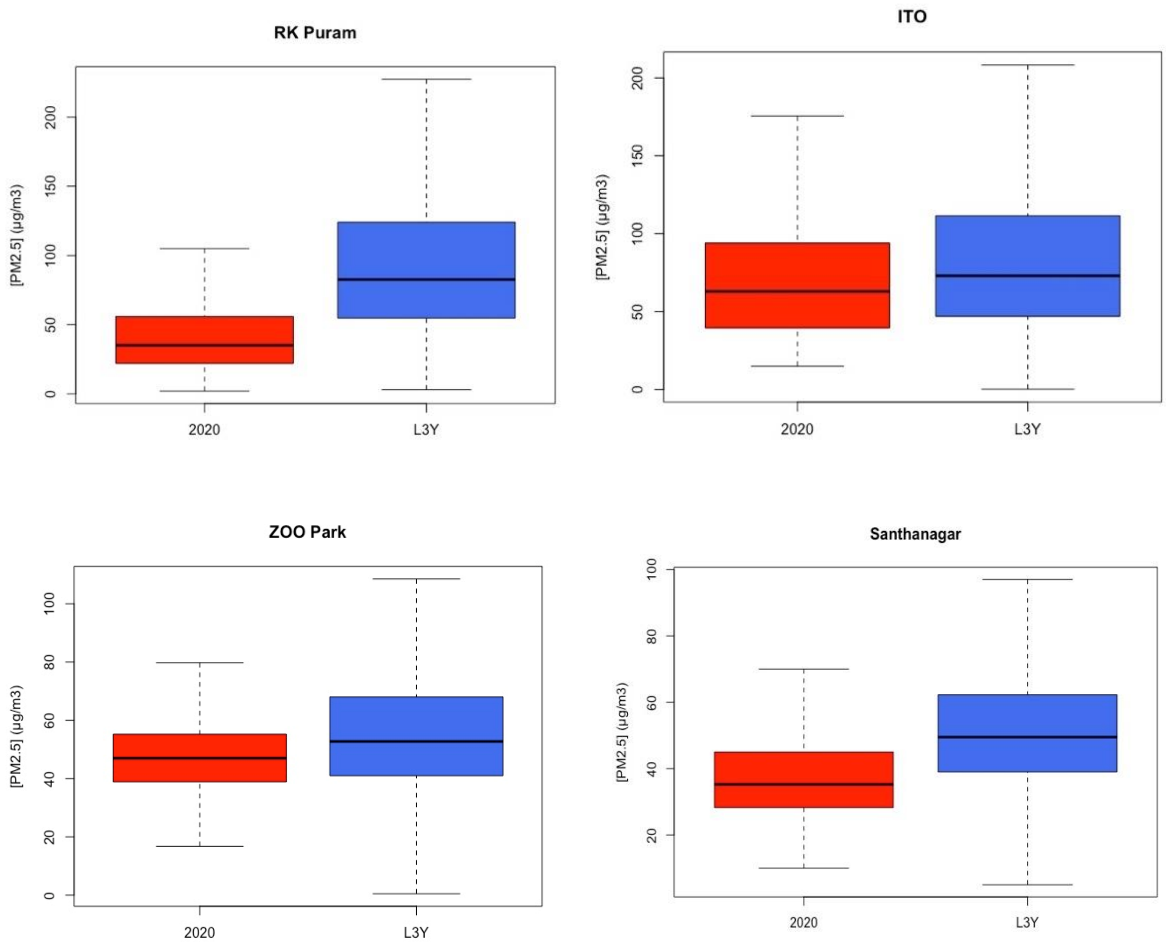


Fig 2: Box plots of hourly measured $PM_{2.5}$ mass loadings at the sites of interest in Delhi and Hyderabad comparing them during phase-I lockdown (24 March to 24 April 2020) to the corresponding dates in 2017-2019 (L3Y). Note the different y-axis for each plot.

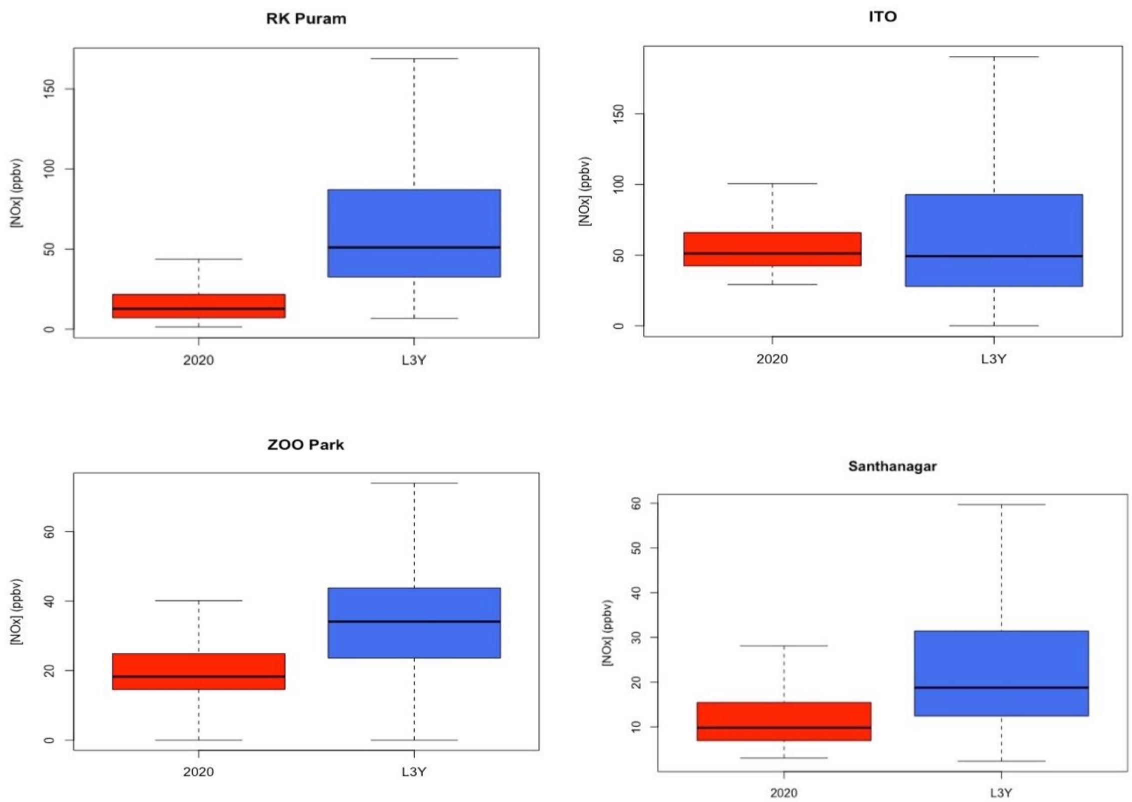


Fig 3: Box plots of measured NOx mixing ratios at the sites of interest in Delhi and Hyderabad comparing them during phase-I lockdown (24 March – 24 April 2020) to the corresponding dates in 2017-2019 (L3Y). Note the different y-axis for each plot.

### 3.4 Predicted levels from BRT model compared to measured concentrations during phase-I lockdown

Using the BRT model, we predicted levels of NOx and $PM_{2.5}$ based primarily on the meteorology at each site for Feb-Apr 2020, in order to capture the changes between pre-lockdown and phase-I lockdown periods. The predicted values from the model can be considered as representative of the expected levels during phase-I lockdown, and any difference between predicted and measured may be attributed to changes in local emissions [19]. We compared the predicted and measured levels at each site, and as a summary we present the mean diurnal trends in Figs 4-5. The time series of predicted and measured levels pre- lockdown and phase-I (Feb-Apr 2020) are shown in the Supporting Information (Figs S3 and S4). From Figs 4 and 5, the model performed well in predicting measured levels and capturing the temporal trends prior to lockdown at each site for $PM_{2.5}$ ($r^2$ of 0.61-0.93) and NOx ($r^2$ of 0.76-0.9).

The predicted $PM_{2.5}$ mass concentration diurnal trends in phase-I lockdown are similar to those measured at all sites (Figs 4). The difference in $PM_{2.5}$ levels after weather normalization during phase-I lockdown compared to pre-lockdown was 8%, -0.6% and 3% for RK Puram, ITO and Zoo Park, respectively. Thus, the changes in $PM_{2.5}$ mass concentrations observed at these sites during phase-I lockdown was likely less attributable to local emissions, but rather due changes meteorology. The importance of meteorology on $PM_{2.5}$ levels suggests regional sources may play a significant role.

Differences in NOx mixing ratios were observed between mean diurnal predicted and measured levels during phase-I lockdown at two sites (Figs 5). The difference in mean diurnal trends pre-lockdown compared to phase-I lockdown for NOx was on average was 20%, 5% and 30% at RK Puram, ITO and Santhanagar, respectively. At RK Puram, the measured NOx levels were notably lower than predicted during the afternoon (12-6pm), with average reductions of 50%, while at ITO and Santhanagar, the reduction was 5.5% and 33%, respectively, similar to the daily mean difference. There was a notable difference in predicted reduction in NOx during phase-I lockdown between the two sites in Delhi. At RK Puram, there was a large difference between predicted and measured NOx, while predicted and measured NOx levels at ITO were similar. Both sites are near major roads and the reason for this difference was likely the prevailing wind direction with respect to this major source. During phase-I lockdown the prevailing wind direction was west/northwest (Fig S5, Supporting Information). Under these conditions, the RK Puram site was downwind and the ITO site was upwind from major roads. Therefore, while lower NOx levels are observed during phase-I lockdown at ITO, this is predicted by the model based on the meteorology, and this is perhaps best illustrated by the flat diurnal cycle in observed NOx during phase-I lockdown (Fig 5), atypical if vehicle emissions were dominant. In the pre-lockdown period, when there was significant portion of wind from east (placing the site downwind from major roads, Fig S5), the model performed well at capturing the NOx diurnal trends that are more typical for vehicle emissions at ITO. However, without detailed traffic activity data for these two locations it is difficult to ascertain the true cause of the differences, but what is clear is that the changes in meteorology affected the observed levels.

Overall, we observed a greater difference between predicted and measured levels with NOx compared to $PM_{2.5}$, and this likely reflects that NOx is a primarily emitted by sources most affected by phase-I lockdown (i.e. vehicle exhaust emissions). The reduction in NOx emissions would also affect chemical processes, notably ozone production, which is discussed in more detail in the next section.

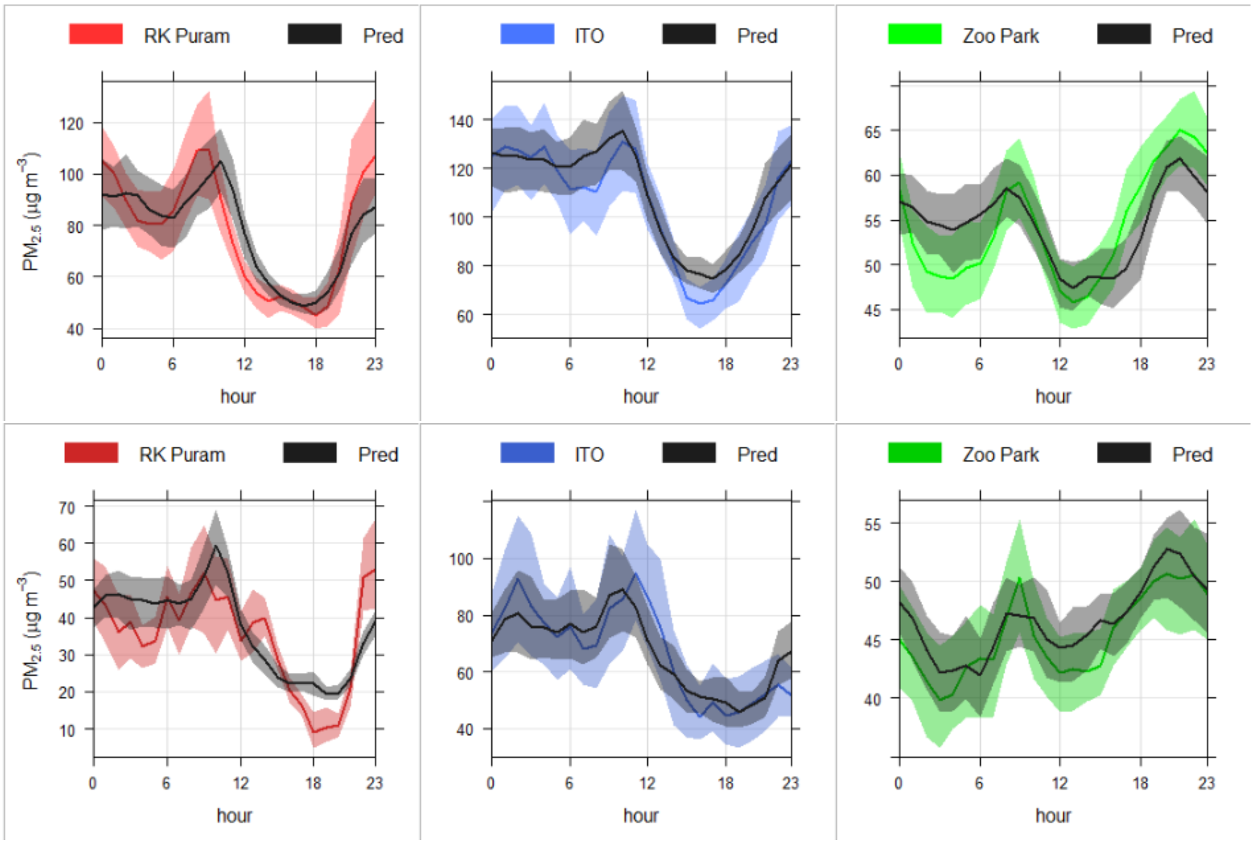


Figure 4. Diurnal trends of measured $PM_{2.5}$ mass concentrations and predicted levels pre-lockdown (top) and during phase-I lockdown (bottom) at the three sites.

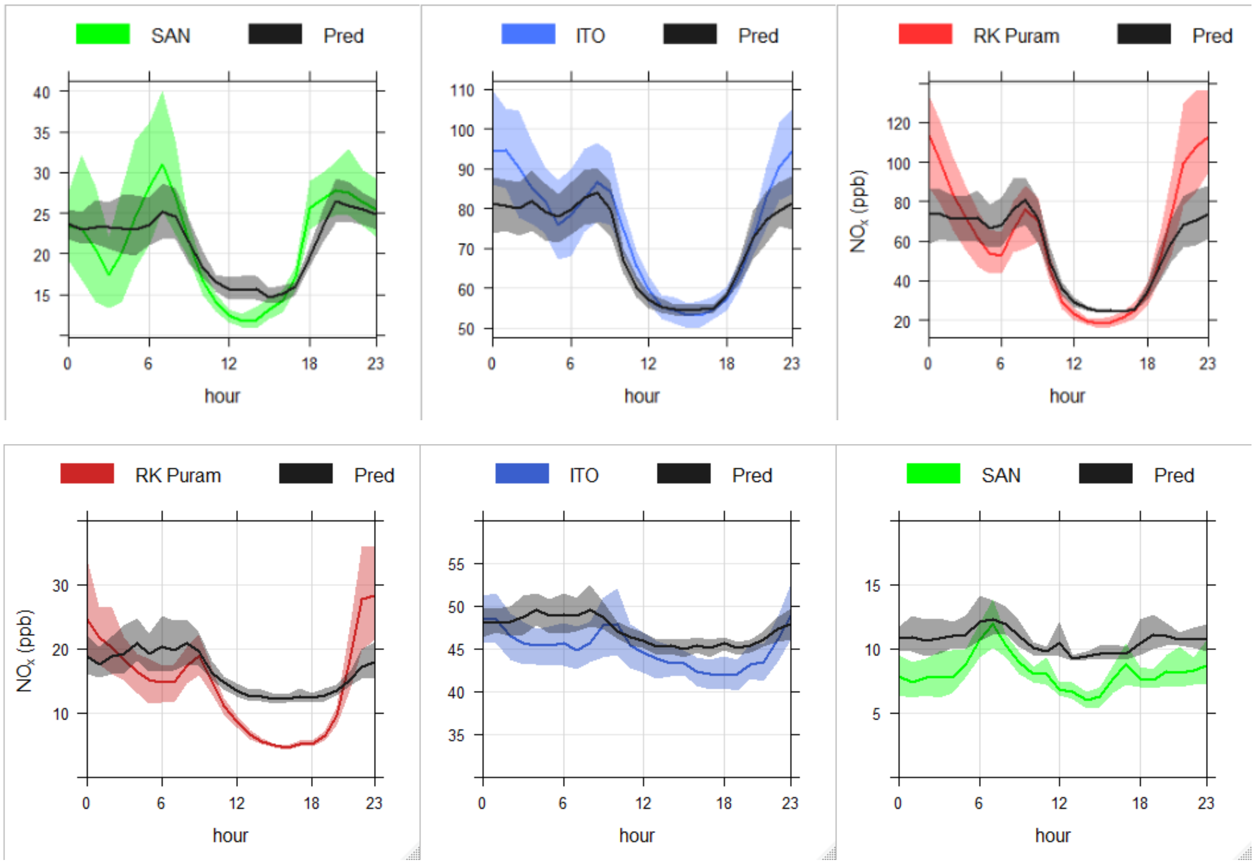


Fig 5: Diurnal trends of measured NOx mixing ratios and predicted levels pre-lockdown (top) and phase-I lockdown(bottom) at the three sites.

## 3.5 Effect of lockdown on atmospheric chemistry: Evidence for local ozone production in Delhi being VOC-limited

The phase-I lockdown provided an opportunity to observe the impacts of a different chemical regime on local ozone production. At all sites, $O_3$ levels increased following the lockdown (Figure S6). However, at the RK Puram site, $O_3$ mixing ratios increased significantly following for all daytime hours in the 17 days during phase-I lockdown compared to the 51 days prior to lockdown (paired t-test for hourly data, Figure 6, Figure S7, Figure S8), corresponding to a maximum average increase of 62% at 15:00. For this site, we examined the potential impacts of NOx, VOCs, and light availability on the chemical formation of $O_3$. As described above, NOx mixing ratios decreased following lockdown (Figure 6). Mixing ratios were statistically lower for all hours of the day (paired t-test for hourly data). Measurements of VOCs were not publicly available from RK Puram, so we collected benzene, toluene and ethylbenzene (collectively referred to as BTE) measurements from the nearby Sirifort site (3 km away). Although this does not represent the full spectrum of VOCs in Delhi, recent work has shown that aromatic compounds comprise the largest fraction of VOCs in Delhi and are predominately from traffic and solid fuel burning emissions [26]. In addition, the $O_3$ formation potential of BTE is high[27], thus BTE can be a useful proxy for the impact of VOCs on local $O_3$ formation. Reported levels of BTE were statistically lower during phase-I lockdown for all daylight hours (paired t-test for hourly data). Daytime visibility (Safdarjung airport, 3.3

km from RK Puram) was generally higher during phase-I lockdown, although data reporting frequency was insufficient to compare to pre-lockdown period statistically (Figure S9). This is generally consistent with a decrease in $PM_{2.5}$ during phase-I lockdown.

Decreased levels of NOx and VOCs during phase-I lockdown, along with increased light, led to increased $O_3$ at the RK Puram site in Delhi. These results agree with recent modelling work that predicted $O_3$ formation in Delhi is in the traditionally defined VOC limited regime[28]. Although VOC limited is the most common descriptor for this regime, it can also occur in areas with high VOC levels [29]. A VOC limited regime may be described as NOx saturated or radical limited with respect to $O_3$ production, in which emissions of NOx exceed radical production (from VOC oxidation and other sources). Chen et al. (2020) also noted the impact of visibility on $O_3$ formation, suggesting the chemistry was light limited, which is consistent with a radical-limited regime. A decrease in NOx leads to increased $O_3$ formation in a radical-limited regime because of a reduction in the loss pathway for radicals through reaction with $NO_2$. Similar observations of increased $O_3$ resulting from pandemic-related decreased NOx were made in urban areas in China [13] and the UK [30].

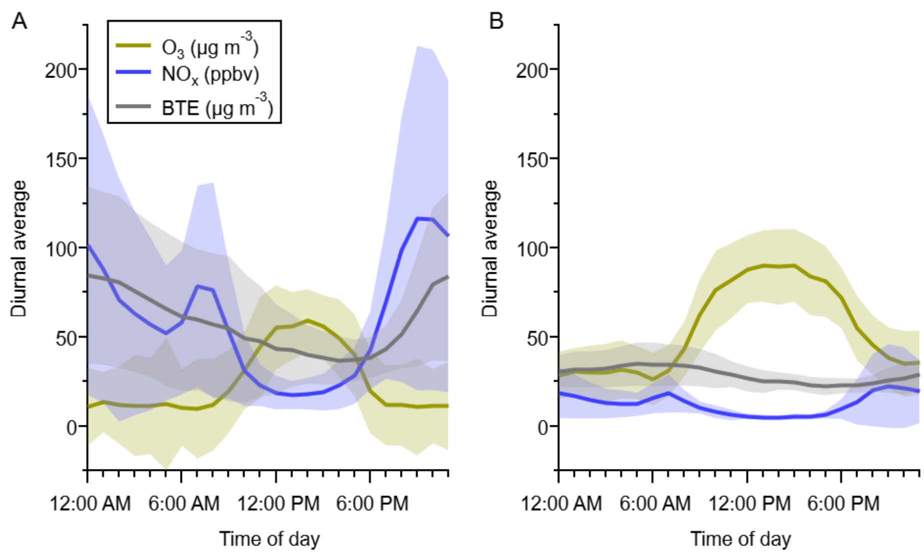


Fig. 6: Diurnal averages of $O_3$, NOx, and the sum of benzene, toluene, and ethylbenzene (BTE) in RK Puram in the (A) 51 days preceding lockdown and (B) 17 days following start of phase-I lockdown. Shaded areas represent the standard deviation of the measurements.

## 4.0 Conclusions

Indian cities can experience severe air pollution from a complex mixture of sources, and the reduction in activity during the COVID-19 lockdown offered a natural experiment to study the contribution of local sources in urban areas. The concentrations of NOx and $PM_{2.5}$ were observed to decrease during phase-I lockdown in both Delhi and Hyderabad at all selected sites, as would be expected if local emissions were driving ambient levels at these sites. Compared to previous years, the calculated reduction in median concentrations during phase-I lockdown period was generally large, up to 57% and 75% for $PM_{2.5}$ and NOx, respectively. This calculation assumes that the local emission solely controls ambient levels, yet meteorology also impacts air quality. To normalize for its effect, we employed a BRT model to predict concentrations based on meteorology and compared this to measured values during phase-I lockdown.

The calculated reduction in $PM_{2.5}$ and NOx levels during phase-I lockdown using a BRT model to account for effect of meteorology (Figs 4 and 5) were notably different to those calculated by comparing median concentration during phase-I lockdown to the same time period in previous years (Table 1). While the relative trends were similar, with both methods suggesting smaller change during phase-I lockdown at ITO compared to RK Puram and the Hyderabad sites (Table 1 and Figs 4 and 5) the absolute magnitude differed. Overall, a higher percentage reduction was calculated in comparing median concentrations (Table 1) than when the effects of meteorology were normalized by the BRT model. This would suggest that, despite lower concentrations being observed at all sites for $PM_{2.5}$ and NOx during phase-I lockdown compared to pre-lockdown (Fig 1), much of the observed decrease after lockdown was, at least in part, driven by changes in meteorology.

For $PM_{2.5}$, after normalization due to meteorology the calculated reduction during phase-I lockdown was small (Fig 4). Thus, the changes in $PM_{2.5}$ mass concentrations observed in Delhi and Hyderabad during phase-I lockdown (at least for the sites studied) were likely less attributable to local emissions, but rather due changes in background levels (i.e. regional source(s)). This result stands in contrast to previous work based on solely on observational data in Delhi, which concluded significant reductions due to lockdown (<60%, [7] and references therein). But this result is perhaps not surprising when considering the significant influence of regional sources on $PM_{2.5}$ levels across northern India [20]. These sources include rural/agriculturally based emissions, that were possibly less affected by lockdown [26].

While for NOx the reduction during phase-I lockdown varied by site (on average 5-30%, Fig 5), likely reflecting differences in local source emissions and its relative proximity to the monitoring station, highlighting the importance of meteorology (i.e. wind direction) on the observed levels. Overall, we observed a greater difference between predicted and measured levels with NOx compared to $PM_{2.5}$, and this likely reflects that NOx is a primarily emitted by sources most affected by lockdown (e.g. vehicle exhaust emissions). Changes in relative amounts of precursor concentrations led to observed increased in $O_3$ post-lockdown at both sites in Delhi. Consistent with previous modelling work, $O_3$ in Delhi was shown to be in the VOC limited regime (also known as radical limited). Decreased levels of NOx and increased light led to increased $O_3$ in the phase-I lockdown. This emphasizes the need for clear consideration of chemistry when targeting emissions reductions. Reductions in NOx and $PM_{2.5}$ can lead to increased $O_3$ formation in Delhi, which indicates potential trade-offs in emissions reduction.

The presented changes in air pollutant levels during phase-I lockdown in the current work cannot be extrapolated to be solely from reduction in emissions activity and instead reflects the complex interactions between emissions, meteorology and chemistry. This work highlights that the impacts of all three must be considered when assessing the effects of a short-term intervention on air pollutants.

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## Author contributions

LRC conceptualized the study. YEI performed the modelling. All authors contributed to data analysis, manuscript writing, and editing.

## Conflicts of Interest

There are no conflicts of interest to declare.

## References


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***Supporting information for***

# Importance of meteorology and chemistry in determining air pollutant levels during COVID-19 lockdown in Indian cities

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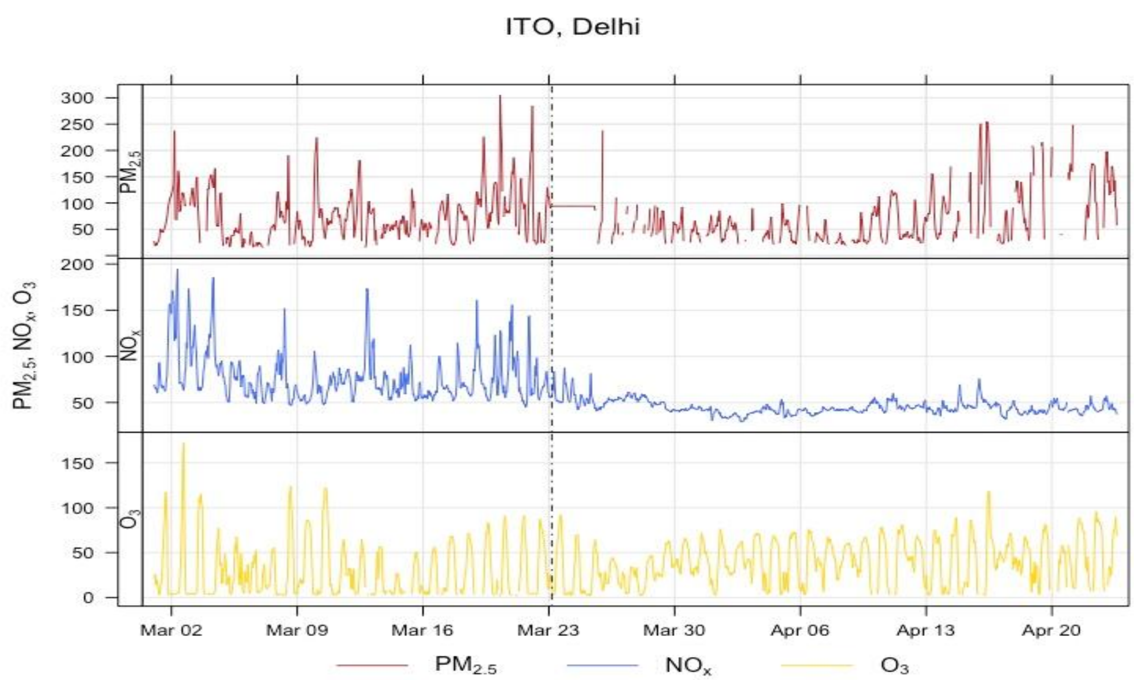



Figure S1: A time series of $PM_{2.5}$ (µg/m$^3$), NOx (ppbv) and $O_3$ (µg/m$^3$) levels pre-lockdown and during phase-I lockdown at ITO, Delhi. The marker placed on 23 March denotes the start of phase-I lockdown.

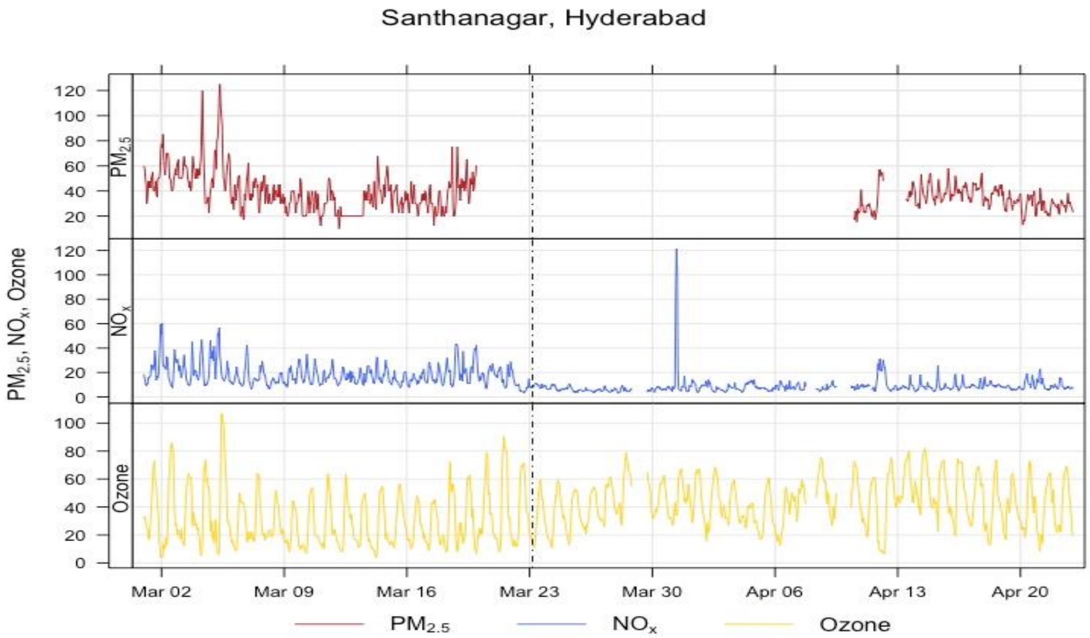
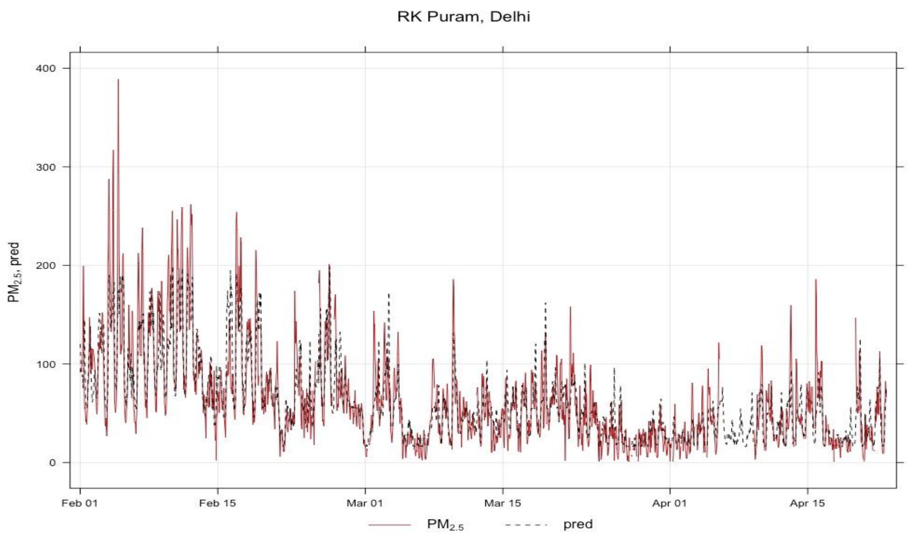



Figure S2: A time series of $PM_{2.5}$ ($\mu g/m^3$), NOx (ppbv) and $O_3$ ($\mu g/m^3$) levels pre-lockdown and during phase-I lockdown at Santhanagar, Hyderabad. The marker placed on 23 March denotes the start of phase-I lockdown.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PM2.5, pred
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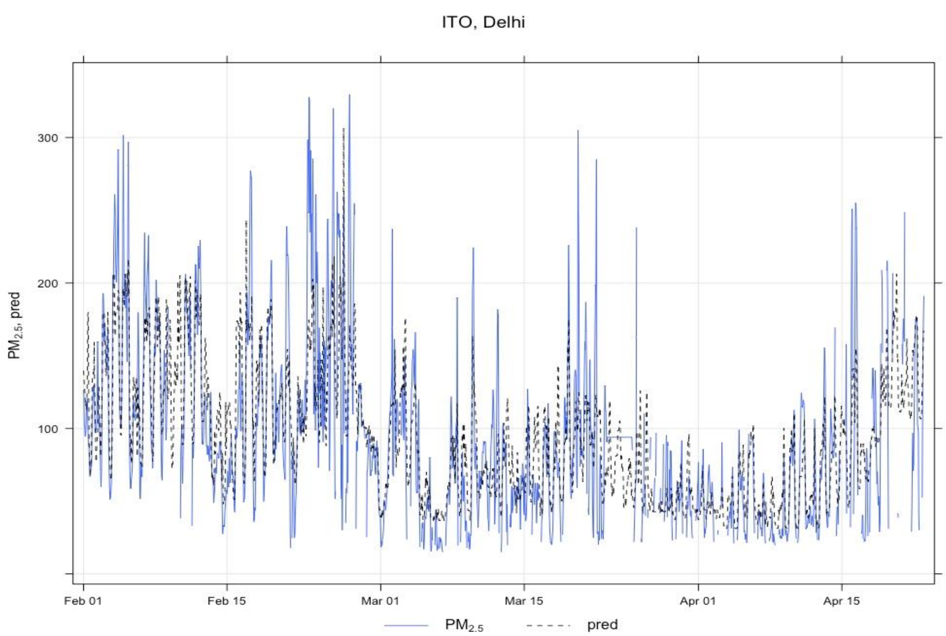
100
200
300
400
Feb 01
Feb 15
Mar 01
Mar 15
Apr 01
Apr 15
PM2.5
pred


ITO, Delhi
PM2.5, pred
100
200
300
Feb 01
Feb 15
Mar 01
Mar 15
Apr 01
Apr 15
PM2.5
pred

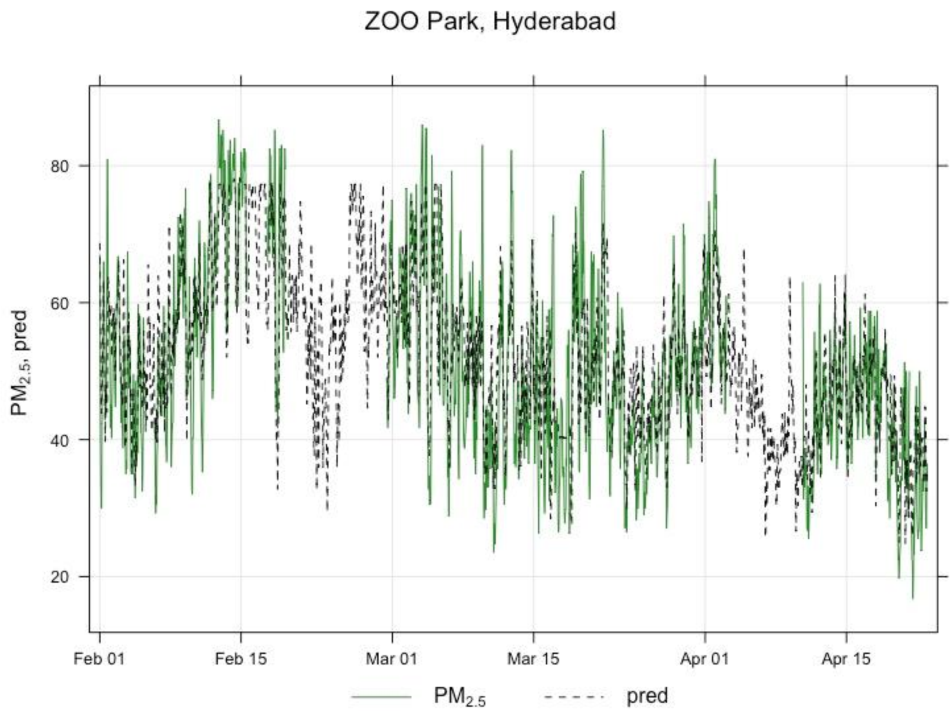
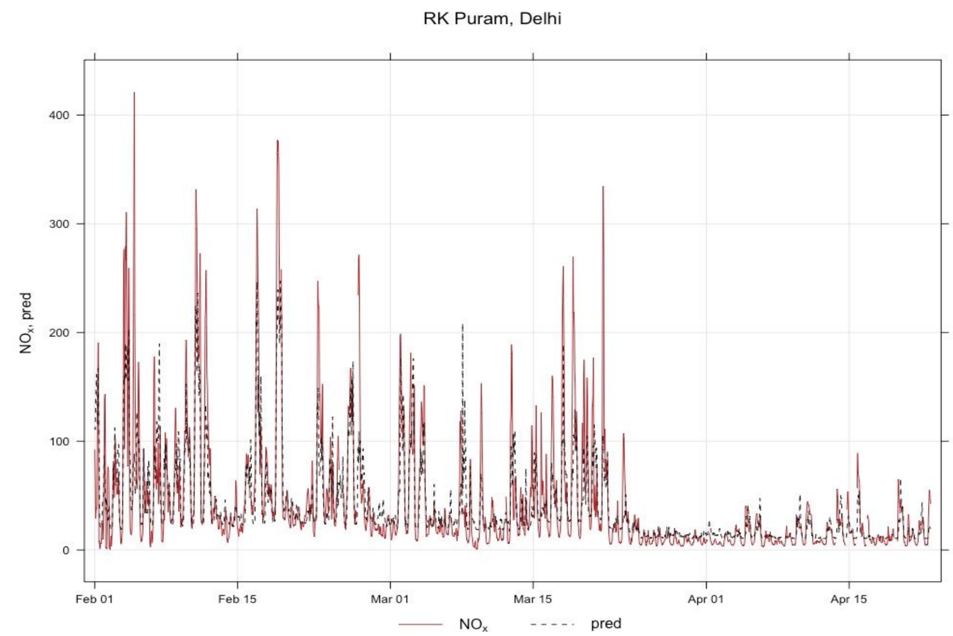
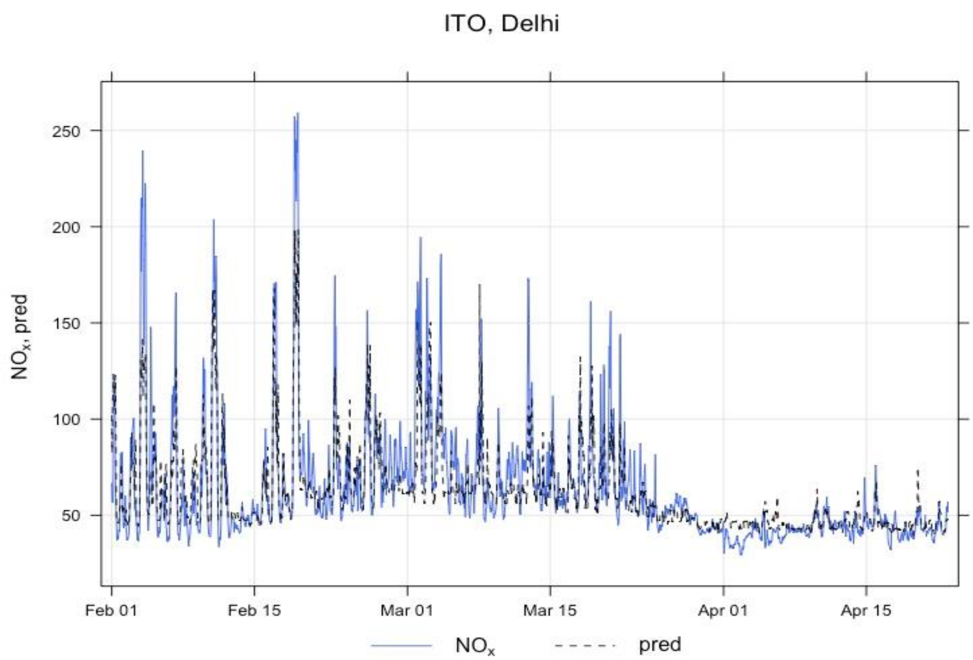



Figure S3: Time series of measured and predicted $PM_{2.5}$ mass concentrations pre-lockdown and during phase-I lockdown at RK Puram (Delhi), ITO (Delhi) and Zoo Park (Hyderabad).


RK Puram, Delhi
$NO_x$, pred
400
300
200
100
0
Feb 01
Feb 15
Mar 01
Mar 15
Apr 01
Apr 15
$NO_x$
pred


ITO, Delhi
$NO_x$, pred
250
200
150
100
50
Feb 01
Feb 15
Mar 01
Mar 15
Apr 01
Apr 15
$NO_x$
pred

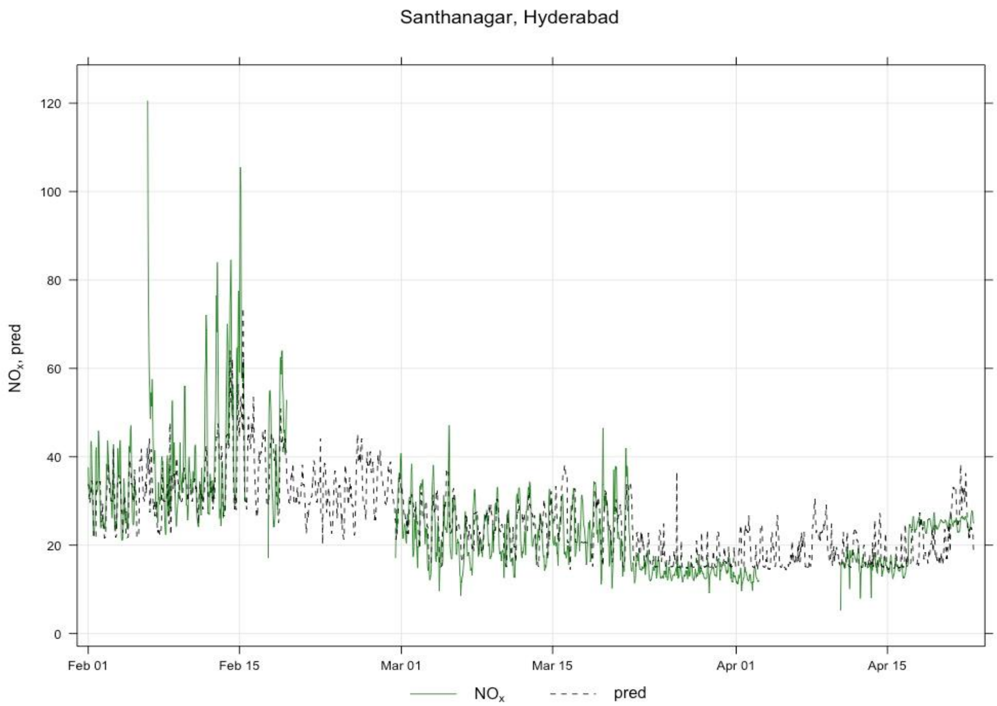



Figure S4: Time series of measured and predicted NOx mass concentrations pre-lockdown and during phase-I lockdown at RK Puram (Delhi), ITO (Delhi) and Santhanagar (Hyderabad).

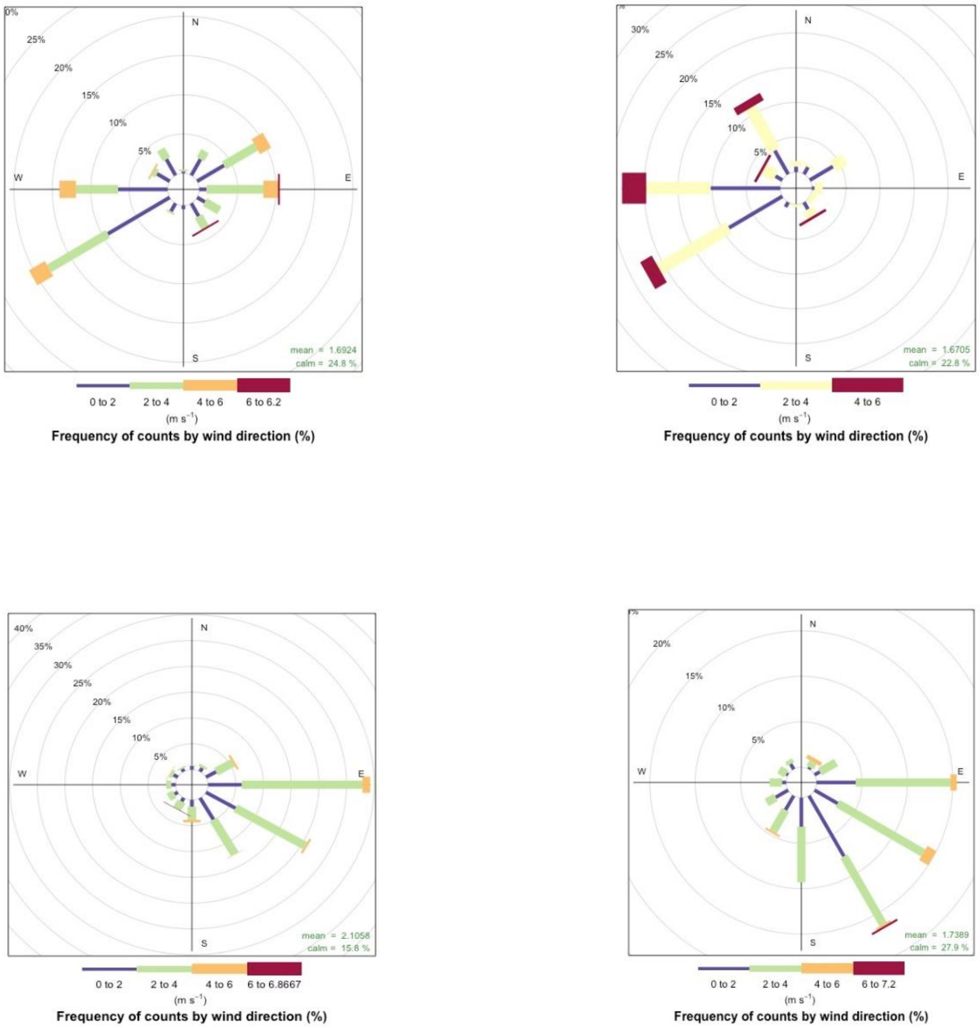



Figure S5: Wind rose plot for pre-lockdown and during phase-I lockdown period at Safdarjung airport (Delhi – top) and Begumpet airport (Hyderabad – bottom) (Feb-Apr 2020).

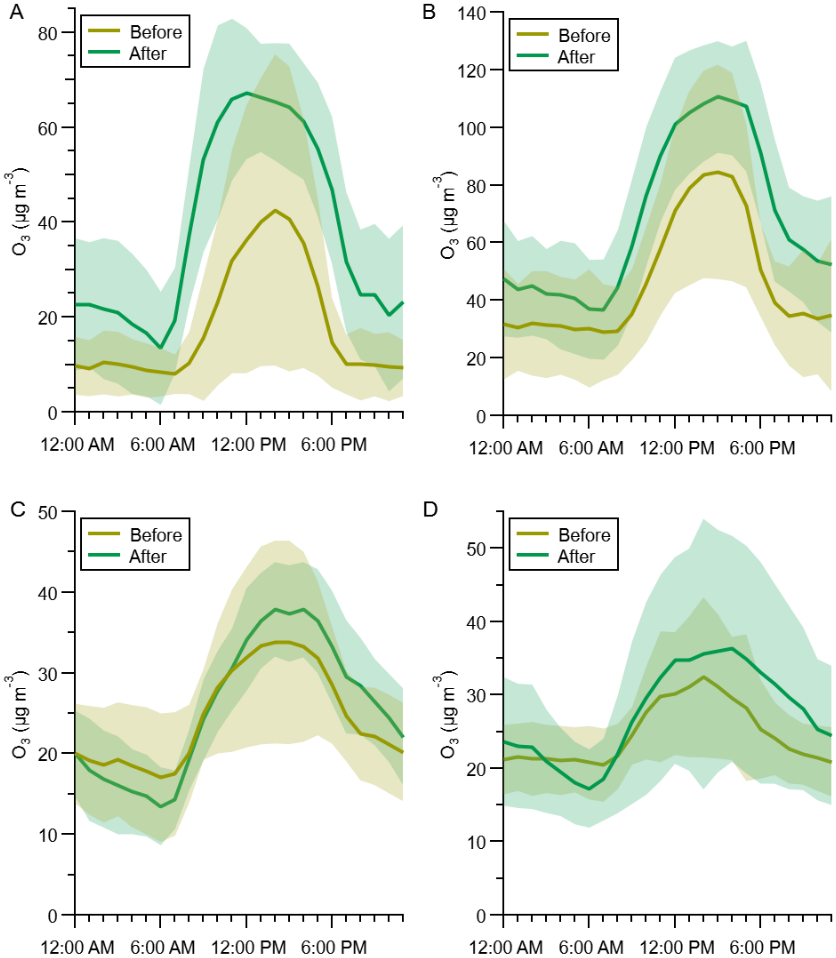



Fig S6: Comparison of diurnally-averaged $O_3$ pre-lockdown and during phase-I lockdown at: (A) ITO, (B) DTU, (C) ICRISAT, and (D) Zoo Park sites.

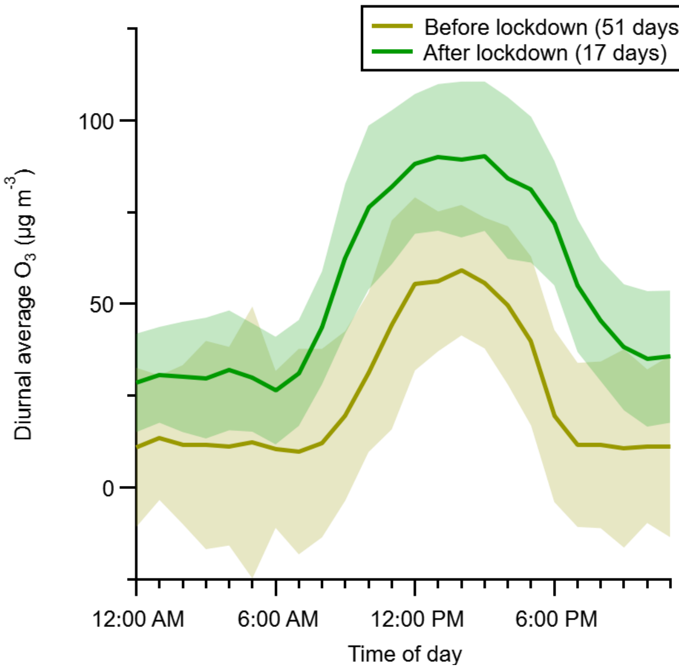



Fig S7: Comparison of diurnally-averaged O3 pre-lockdown and during phase-I lockdown at RK Puram. Shaded areas represent the standard deviation.

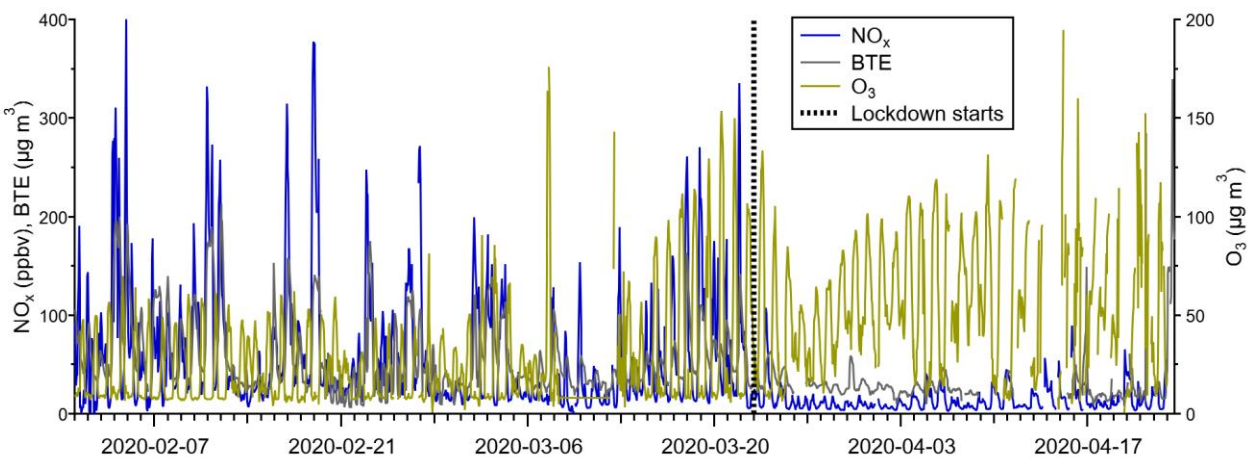



Fig S8: Time series of $O_3$, NOx, and the sum of benzene, toluene, and ethylbenzene (BTE) from RK Puram. The vertical line indicates the start of the lockdown.

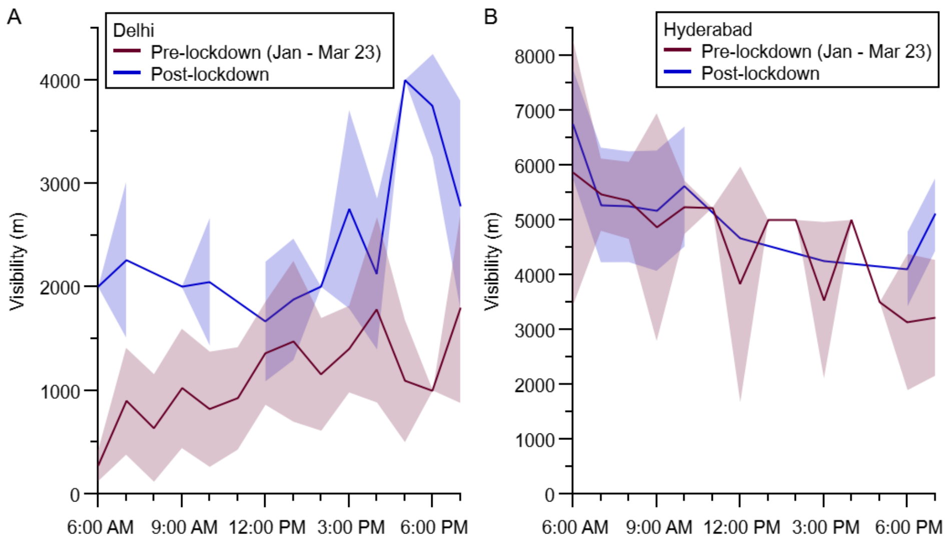



Fig S9: Comparison of visibility measurements before and after the lockdown at: (A) Safdarjung Airport, Delhi, and (B) Begumpet Airport, Hyderabad.