Temporary reduction in fine particulate matter due to ‘anthropogenic emissions switch-off’ during COVID-19 lockdown in Indian cities

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Temporary reduction in fine particulate matter due to ‘anthropogenic emissions switch-off’ during COVID-19 lockdown in Indian cities

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Graphical abstract

Highlights

• COVID-19 lockdown reduced PM$_{2.5}$ concentrations in five Indian cities by up to 54%.
• PM$_{2.5}$ reduction in Delhi was similar to that of other Asian and European cities.
• Modelling revealed fewer extreme PM$_{2.5}$ values during the lockdown in all cities.
• Spatial distribution of AOD showed a general decrease in aerosol loading.
• PM$_{2.5}$ reductions prevented ~630 premature deaths, valued at 0.69 billion USD.
Abstract

The COVID-19 pandemic elicited a global response to limit associated mortality, with social distancing and lockdowns being imposed. In India, human activities were restricted from late March 2020. This ‘anthropogenic emissions switch-off’ presented an opportunity to investigate impacts of COVID-19 mitigation measures on ambient air quality in five Indian cities (Chennai, Delhi, Hyderabad, Kolkata, and Mumbai), using in-situ measurements from 2015 to 2020. For each year, we isolated, analysed and compared fine particulate matter (PM$_{2.5}$) concentration data from 25 March to 11 May, to elucidate the effects of the lockdown. Like other global cities, we observed substantial reductions in PM$_{2.5}$ concentrations, from 19-43\% (Chennai), 41-53\% (Delhi), 26-54\% (Hyderabad), 24-36\% (Kolkata), and 10-39\% (Mumbai). Generally, cities with larger traffic volumes showed greater reductions. Aerosol loading decreased by 29\% (Chennai), 11\% (Delhi), 4\% (Kolkata), and 1\% (Mumbai) against 2019 data. Health and related economic impact assessments indicated 630 prevented premature deaths during lockdown across all five cities, valued at 0.69 billion USD. Improvements in air quality may be considered a temporary lockdown benefit as revitalising the economy could reverse this trend. Regulatory bodies must closely monitor air quality levels, which currently offer a baseline for future mitigation plans.

List of Abbreviation

AOD  Aerosol optical depth
AQI  Air quality index
CO  Carbon monoxide
CO$_2$  Carbon dioxide
COVID-19  Coronavirus disease 2019
1. Introduction

COVID-19, the novel coronavirus disease caused by SARS-CoV-2 (severe acute respiratory syndrome coronavirus 2), was first identified in the Hebei district of Wuhan (China) in December 2019. This infectious disease spread rapidly from China to other countries across the world, and the outbreak was declared a global pandemic on 12 March 2020 by the World Health Organization (WHO, 2020a). The ongoing pandemic has disrupted the lives of billions of people and caused more than 278,994 deaths worldwide as of 11 May 2020 (WHO, 2020b). The United States of America (USA), the United Kingdom (UK), and Italy have experienced the greatest impact to date (11 May 2020), with death tolls of around 76,916, 31,855, and 30,560, respectively (WHO, 2020b). Asian countries, such as India, are not spared where the population density is high (Kumar et al., 2013) and the spread of COVID-19 is yet to reach its peak.

The first case of COVID-19 in India was reported on 30 January 2020 in Kerala, a southern state (PIB, 2020). After a preventive social distancing initiative on 22 March 2020 in the form

**Keywords:** Coronavirus pandemic; SARS-CoV-2 Virus; Air pollution; Health and economic impacts; PM$_{2.5}$ concentration; Emission switch-off

VSL    Value of statistical life
WHO    World Health Organization
of a 14-hour self-quarantine curfew called the ‘Janata Curfew’, the Government of India (GoI) announced a complete lockdown of both internal and external borders, and social isolation measures came into effect on 25 March 2020 for the entire 1.3 billion population to prevent the spread of COVID-19. The lockdown has been renewed four times to date, with the first, second, third, and fourth phases ending on 14 April, 03 May, 17 May, and 31 May 2020, respectively (see details in Section 2.2). As of 11 May 2020, the total number of cases reported in India stands at 67,152, with 40,917 recoveries and 2,206 deaths (COVID-19.in, 2020).

Similar COVID-19 lockdowns throughout the world have entailed self-isolation, reduced personal travel and outdoor activities, and business closures across all sectors, including: commercial; industrial; construction; transport - both road and air; academic; retail; and social, such as restaurants, theatres, cinemas and sports stadiums. Global action to mitigate the pandemic has consequently involved switching off most pollutant emission sources. Therefore, we refer to the COVID-19 outbreak here as an ‘anthropogenic emissions switch-off’ that somehow indicates a pollution baseline, which cities may aim to achieve under ‘normal’ conditions. This switch-off offers important educational opportunities regarding potential control systems and regulations for improved urban air quality in the future. Besides a few exceptional pollution episodes, such as increased levels of fine particulate matter (PM$_{2.5}$, with aerodynamic diameter ≤2.5µm) in the central United States in March due to long-range transport of particles from agricultural burning in Mexico (Schiermeier, 2020), many cities worldwide have seen blue skies for the first time in several decades. This is illustrated by Table 1, which shows appreciable gaseous and PM concentration reductions of up to 77% (in NO; São Paulo, Brazil) and 60% (in PM$_{10}$; Delhi, India) across cities worldwide during the lockdown periods.
Beyond coming into contact with an infected person’s coughing/sneezing or touching contaminated surfaces (Kumar and Morawska, 2019), poor indoor ventilation has also been linked to COVID-19 spread (Brittian et al., 2020; Morawska and Cao, 2020) and outdoor aerosols containing viral RNA (Setti et al., 2020). For example, Li et al. (2020a) reported the prolific spread of COVID-19 in a poorly ventilated restaurant in Wuhan, China. In another study, Liu et al. (2020) examined the potential for aerosol-assisted transmission of the virus by measuring viral RNA in different places inside two Wuhan hospitals in February and March 2020. They reported a high concentration of viral RNA that matched peaks in both sub- and super-micrometre particle ranges and highlighted the potential transmission of SARS-CoV-2 via aerosols. Similarly, Setti et al. (2020) reported the RNA of COVID-19 in the aerosol particles in Italy. Although it is not yet known whether or not this coronavirus interacts with airborne aerosol particles and much needs to be understood in this respect. The individual impact of COVID-19 is greatest for those with weak immune systems, such as the elderly, and those with pre-existing health conditions. For example, Wu et al. (2020a) reported that a COVID-19-infected person >59 years of age has a 5.1-times higher risk of dying, compared with only 0.6-times for those <39 years old. The analogy that air pollution is linked with respiratory and cardiovascular disease (Heal et al., 2012) and that cities with high air pollution may expect to experience a more prominent impact of COVID-19 is hypothesised. Early evidence supports this hypothesis, albeit based on several assumptions. For example, Zhu et al. (2020) applied generalised additive models and reported a 2.24% increase in COVID-19 confirmed cases for each 10 μg m$^{-3}$ increase in PM$_{2.5}$ concentrations across Chinese cities. Likewise, a nationwide cross-sectional study in the US associated an increase of 1 μg m$^{-3}$ in PM$_{2.5}$ concentration with an 8% increase in COVID-19 death rates (Wu et al., 2020b). While links to reduced air pollution during lockdown with human health impacts can be understood,
linking COVID-19 with air pollution and death rates together is still a grey area that will require detailed scientific assessments for developing a consensus.

India faces air pollution challenges due to its explosive population growth and rapid expansion of industrial development in recent decades. As a result of economic growth, air pollutant concentrations have reached alarming levels that consistently exceed ambient air quality standards. This has exacerbated human health risks and increased premature mortality in surrounding communities (Guo et al., 2017; Mukherjee and Agrawal, 2018; Shukla et al., 2020; Sharma et al., 2020). For example, 77% of the Indian population in 2017 were exposed to annual mean ambient PM$_{2.5}$ concentrations of more than 40 µg m$^{-3}$ (ICMR-PHI-IHME, 2017). PM$_{2.5}$ is predominantly generated from sources as by vehicle combustion engines, residential/industrial fuel burning and the secondary aerosol formation (Kumar et al., 2017; Guo et al., 2017; Guo et al., 2019; Hama et al., 2020). In India, studies on air quality changes associated with COVID-19 are limited but clearly show an appreciable reduction in criteria air pollutants (e.g. PM$_{10}$, PM$_{2.5}$, CO, NO$_2$, O$_3$, SO$_2$, and NH$_3$), mainly due to decreased on-road vehicles and closure of non-essential industries (Mahato et al. 2020; Sharma et al., 2020). For example, Sharma et al. (2020) used a WRF-AERMOD modeling system to demonstrate an overall decline of 43% in PM$_{2.5}$ during the lockdown of March 2020, when compared with similar months in previous years. Similarly, Mahato et al. (2020) reported a reduction of more than 50% in PM$_{2.5}$ and PM$_{10}$ concentrations, and Venter et al. (2020) linked the first two-weeks of lockdown in India to a reduction in PM$_{2.5}$ related premature mortality of roughly 5300 (Venter et al., 2020). Chennai, Delhi, Hyderabad, Kolkata, and Mumbai are among the most populated (Table S1) and industrialised Indian cities, where ambient concentrations of PM$_{2.5}$ are ordinarily above WHO annual guideline values of 10 µg m$^{-3}$ (WHO, 2016). We have targeted these sprawling Indian cities to understand relative changes in PM$_{2.5}$ concentrations due to the impact of lockdown on emission sources before and during the lockdown.
It may be expected that lockdowns to contain the spread of COVID-19 will generally result in reduced urban anthropogenic emission activities, and one can reasonably expect a reduction in concentrations of primary pollutants during lockdown when compared with periods of business as usual. However, what remained unknown was: how much reduction lockdown led to, in quantitative terms; whether this reduction occurred to a similar degree in all cities; and what additional factors may influence any differences between cities. As illustrated by Table 1, COVID-19 related air quality studies for Indian cities are limited. Such studies have typically covered varying days of the early lockdown period and involved analyses based on publicly available data from monitoring stations (e.g. Mahato et al., 2020; Sharma et al., 2020) and/or modelling exercises (e.g. Mitra et al., 2020). Therefore, varied estimations of PM$_{2.5}$ concentration reductions have been produced for the same cities, such as 35-39% for Delhi (Chauhan and Singh, 2020; Mahato et al., 2020), 30-40% for Kolkata (Mitra et al., 2020), and 14-43% for Mumbai (Chauhan and Singh, 2020; Sharma et al., 2020). We cover the extended duration of lockdown in five Indian cities (Chennai, Delhi, Hyderabad, Kolkata, and Mumbai) and go beyond the scope of previous studies by evaluating the impact of the COVID-19 pandemic’s ‘anthropogenic emission switch-off’, with an aim to: (i) investigate variations and characteristics of PM$_{2.5}$ concentrations during the lockdown in five Indian cities compared to similar periods in the previous five years; (ii) contextualise our own results from Indian cities with others from across the world; (iii) explore potential factors that influence differences between divergent concentration changes in different cities; (iv) monitor the distribution of PM$_{2.5}$ concentrations using theoretical probability density function (PDF) at six different time spans in five Indian cities; (v) reveal a holistic picture of aerosol loadings for each of these cities by utilising aerosol optical depth (AOD) analysis via satellite imagery; and (vi) generate valuations of health and economic impact due to decreased concentrations.
2. Materials and methods

2.1. Study areas

Figure 1 presents the topography of the studied Indian cities (Chennai, Delhi, Hyderabad, Kolkata, and Mumbai). Corresponding tables summarise each city’s location, population, population density and traffic density (Table S1), known sources and traffic contributions to PM$_{2.5}$ (Table S2), and key features and meteorological characteristics (Table S3). All five cities experience the summer season during the lockdown period of March-May (Table S4). Differences in meteorological conditions between this period of 2020 and of previous years were modest (Table S4), as discussed below.

- **Chennai** is the capital city of the south Indian state of Tamil Nadu, with a population of ~10.9 million and an overall population density of 25,754 per square kilometre (Table S1). The average elevation of Chennai above the mean sea level (MSL) is ~15.8 m (Table S3). The city had about 5.3 million vehicles on its roads in 2017 (Table S1). The dominant wind direction, observed from Chennai airport (12°58′56″N 80°9′49″E), is towards the south (21%), followed by the west (16%) and the east (15%) (Table S3). Pollutants from industrial suburbs in North Chennai (Padi, Avadi and Ambattur) are transported by the wind towards the central and southern parts of the city. The average wind speed, ambient temperature and relative humidity (RH) during the lockdown period in 2020 were 3.0±1.7 m s$^{-1}$, 30.6±2.8 °C and 71.7±12.8%, respectively.

- **Delhi** is the capital of India and one of the largest megacities of Asia, with an overall population of 30.29 million and a population density of 20,412 per square kilometre (Table S1), as well as the highest number of registered on-road vehicles of all Indian cities (~10.26 million in 2017; Table S1). Delhi has an average elevation of ~216m. The dominant wind direction, observed at Safdarjung airport (28°35.00’ N, 77°12.48’ E), which is located 3.75km from the geographical centre of Delhi (India gate), is westerly (nearly 34% of the
observed duration during the study period; Table S3). The wind speed, ambient temperature and RH during the lockdown period were 2.5±1.7 m s\(^{-1}\), 31.2±3.1 °C and 43.4±8.6%, respectively.

- **Hyderabad** is the capital city of the south Indian state of Telangana, situated at an altitude of 545m above MSL (Table S3), with a population of ~10 million and an overall population density of 15,391 per square kilometre (Table S1). The rate of urbanization and infrastructural development in the city has increased over the past decade to about 2.71 million vehicles on the roads of Hyderabad in 2017 (Table S1). Dominant wind direction, recorded (during 2000-2019; Table S3) at Rajiv Gandhi Hyderabad International Airport in Hyderabad (17°14.43' N, 78°25.73' E), is towards the west (30%). The wind speed, ambient temperature and RH during the lockdown period were 1.1±0.2 m s\(^{-1}\), 30.5±4.1 °C and 54.9±18.1%, respectively.

- **Kolkata** is the capital city of the East Indian state of West Bengal, and is considered one of the most polluted cities in the world (Scroll, 2019). Kolkata has a population of 14.8 million with an overall population density of 72,439 per square kilometre (Table S1). At just 6.10m above MSL (Table S3), Kolkata is located in the Ganges Delta of north-eastern India, near the Bay of Bengal and ~80km west of the border with Bangladesh. This dense city had about 0.8 million vehicles on the roads in 2017 (Table S1). Observed meteorological data (2000-2019) from Netaji Subhas Chandra Bose International Airport (22°39.24' N, 88°26.80' E), known as Dum Dum airport (located ~17km from Kolkata city centre), showed that wind direction is primarily towards the south (34% of the time). The wind speed, ambient temperature and RH during the lockdown period were 1.0±0.6 m s\(^{-1}\), 29.3±3.6 °C and 69.1±17.7%, respectively.

- **Mumbai** is the sixth-largest metropolitan region in the world (Pacione, 2006) and the financial capital of India. It has a population of 20 million at a density of 33,850 per square
kilometre (Table S1). With an average elevation of ~12.20m above MSL (Table S3), the
dominant wind direction measured at Chatrapati Shivaji Maharaj airport (Terminal-1;
19°5.50' N, 72°51.97' E) is towards the west (36% of the observed duration; Table S3),
which highlights the role of meteorological factors in transporting pollutants from the
eastern manufacturing districts into the city. Ambient air quality in Mumbai is also
significantly affected by vehicle traffic (about 3.05 million on-road vehicles in 2017; Table
S1). The wind speed, ambient temperature and RH during the lockdown period in 2020
were 0.8±0.5 m s⁻¹, 29.5±1.8 °C and 81.4±8.6%, respectively.

2.2 Data source

The hourly PM$_{2.5}$ data for Chennai, Delhi, Hyderabad, Kolkata and Mumbai were
extracted for the period between January 2015 and May 2020 (Section 2.3). These data are
measured using the beta-attenuation monitors that are calibrated and maintained as per the
protocols of the US EPA (EPA, 2009). The beta-attenuation monitoring method for continuous
PM$_{2.5}$ monitoring is used for over 80% of state- and local-level observations in the US (EPA,
2015). The data are available online (https://www.airnow.gov/) and have been used previously
by numerous studies in India (e.g. Chen et al., 2020; Wang and Chen, 2019) and elsewhere
(e.g. Berman and Ebisu, 2020; Dhammapala, 2019; Martini et al., 2015). As a quality assurance
exercise, we applied two approaches (i) outlier detection and gap-filling techniques to the
obtained data set, similar to what Jesus et al. (2020) applied for PM$_{2.5}$ long-term time series
using the forecast package (Hyndman et al., 2019), and (ii) a simpler approach that included
removal of all the zero, negative and invalid data points after the manual inspection of the data
set. The percentage of maximum difference using both approaches between PM$_{2.5}$ mean
concentrations for all cities during the lockdown in the year 2020 were found to be less than
1%. This lower difference was expected since the percentage of total missing data points (i.e.
the sum of zero, negative and invalid) during the assessment period was also less than 1%.
Most of the gap-filling methods are usually recommended when missing data percentages are more than 5\% (Ottosen and Kumar, 2019; Junger and Løen, 2015; Junninen et. al., 2004). Since these differences in concentrations and the percentage of missing data were modest, we adopted a simpler approach (ii) to preserve the site-specific measured data points as-is for further analysis. The cleaned data was run through the R statistical package (R Core Team, 2020) in the Open-air software package version 2.6–5 (Carslaw and Ropkins, 2012; Carslaw, 2015) to identify missing periods and assess basic statistics, and to plot the data at each site for further
2.3 Data analyses

The lockdown period in Indian cities (25 March onwards) is divided into different phases as discussed below. Detailed specifications regarding each phase are presented in the introduction of Section S1. On 22 March 2020 (0700-2100h IST), a 14-hour voluntary public curfew/restraint was imposed as a pre-emptive measure against COVID-19 spread, as suggested by the government. From 25 March 2020 onwards, an official quarantine plan was imposed by the GoI in four phases. Phase I (ended 14 April 2020) involved a suspension of nearly all services for 21 days, including transportation and factories but excluding emergency services. Phase II (15 April 2020 to 03 May 2020) was an extension of Phase I for an additional 19 days, with a conditional relaxation for certain businesses. A lockdown area classification system (Red/Orange/Green) was initiated during this phase on 16 April 2020. Phase III (04 May 2020 to 17 May 2020) remained in place for the subsequent 24 days. Area classification was periodically revised during this phase. Phase IV (18 May 2020 to 31 May 2020), a 14-day quarantine, was the most recently updated rule by GoI before submitting this study. The duration between the official initiation of the lockdown restrictions (25 March 2020) and the time we extracted the datasets (11 May 2020) is henceforth referred to as ‘lockdown’ and was compared with similar periods of the past five years (2015-2019).

2.3.1 Generalized extreme value distribution

The probabilistic distribution of PM$_{2.5}$ exposure concentration during the lockdown period was explored for each city. Estimation of the PDF of PM$_{2.5}$ concentrations before and during lockdown periods was carried out using a generalized extreme value (GEV) model, which is a common statistical approach used in extreme value analysis of air pollution data (Martins et al., 2017). The probability distributions or density function in the GEV distribution model is described by Eq. (1):
\[ f_Y(y; \mu, \sigma, k) = \exp \left\{ - \left[ 1 + k \left( \frac{y-\mu}{\sigma} \right)^{\frac{1}{k}} \right] ^{-\frac{1}{k}} \right\} \]  

(1)

The theoretical density of PM$_{2.5}$ is also estimated using Eq. (1). The variable $y$ is the hourly PM$_{2.5}$ concentration and the parameters $\mu$, $\sigma$, and $k$ represent the distribution location, scale, and shape, respectively. The location determines the position of the distribution, the scale determines the size of deviations around the location parameter, and the shape determines the behaviour of the upper tail of the distribution (Coles, 2001). When $k=0$, Eq. (1) is Gumbel distribution (light tail), when $k$ is positive, Eq. (1) is Frechet distribution (heavy tail) and when $k$ is negative, Eq. (1) is Weibull distribution (upper bounded tail). The estimated shape of PM$_{2.5}$ for each city before and during lockdown is reported in Table S5. The GEV model is fitted to the PM$_{2.5}$ dataset by maximizing the logarithmic likelihood function using the maximum likelihood method (Coles, 2001).

2.3.2 Aerosol optical depth variation

The relation of AOD with atmospheric physics and regional air quality is widely discussed, for example, for stating the correlation between cloud condensation nuclei and AOD (Liu and Li, 2013) or the correlations between PM$_{2.5}$ and AOD (Kim et al., 2014). We perform an analysis (with a top-down approach) using AOD data, that could be useful to provide and link information related to the variation of aerosols during the anthropogenic emissions switch-off over five Indian cities. AOD measures aerosol loading, which is an optical property derived from different earth observation satellites (Li et al., 2009). The AOD spatial distribution maps show monthly average aerosol loadings worldwide, whereas the boundary values of optical thickness range from 0 to 1. An optical thickness of 0.1 is characterised by a crystal-clear sky with maximum visibility and an optical thickness of 1 represents very hazy conditions (NASA, 2020a). The analysed AOD datasets in this estimation, which were extracted from the NASA-Earth Observatory Global maps webpage (https://earthobservatory.nasa.gov/global-maps),
included both Terra- and Aqua-MODIS (Moderate Resolution Imaging Spectroradiometer) with a resolution of \(0.1^\circ \times 0.1^\circ\). The Terra- and Aqua-MODIS instruments scan the same area of Earth, with three-hours apart (NASA, 2020b). According to the Space Science and Engineering Centre (SSEC, 2020a), the Terra satellite crossing times in India (local time) approximately range from 0900 to 1100h and from 2100 to 2300h. For the Aqua satellite, approximate crossing times are from 0100 to 0300h and from 1200 to 1400h (SSEC, 2020b). For this study, a comparison analysis was carried out on monthly averaged AOD of both Terra- and Aqua-MODIS datasets during the lockdown period. March 2020 (before-lockdown) and April 2020 (during-lockdown) were selected as the reference periods for the analysis. The comparison analysis was obtained by means of the AOD variation, calculated as follows:

\[
AOD_{\text{variation}} = \left[ \frac{(AOD_i - AOD_{ref})}{AOD_i} \right] \times 100
\]  

(2)

where \(AOD_i\) and \(AOD_{ref}\) represent a comparison month (during-lockdown) and the reference month (before-lockdown), respectively.

### 2.3.3 Health impact assessment and economic valuation

Impacts of reduced PM\(_{2.5}\) pollution, such as averted health burden (HB, in terms of premature deaths) related to PM\(_{2.5}\) exposure reductions and associated economic outcomes, have attracted worldwide attention, as summarised in Table S6. We have undertaken health impact assessments and economic valuations regarding PM\(_{2.5}\) concentration reductions via a two-step approach: firstly, by estimating HB (Eq. 3) and the excess risk (ER) of premature mortality (Eq. 6); and secondly, by determining the value of associated economic cost (million USD per year) for the selected Indian cities during lockdown (25 March to 11 May 2020), as compared to similar periods of 2015-2019.

HB due to short-term exposure to PM\(_{2.5}\) (number of premature deaths; Eq. 3) was estimated for the lockdown period (HB\(_{LP20}\); 25 March to 11 May 2020) and for the lockdown equivalent
period during 2015-2019 (HB_{LEP15-19}). The reduction in health burden (ΔHB), based on averaged daily mean PM$_{2.5}$ concentrations, is calculated as a difference of the former and latter HB estimates (Eq. 4), following the approach applied in previous studies (Sahu and Kota, 2017; Chen et al., 2020; Sharma et al., 2020; Venter et al., 2020). Likewise, the potential health benefits due to changes in daily mean PM$_{2.5}$ concentrations (averaged over the lockdown, 25 March to 11 May 2020, and over the lockdown equivalent period of each previous year from 2015) in each city were estimated using the relative risk (RR) and ER associated with the pollutant loads (Eqs. 5 and 6).

$$\text{HB} = \text{BM} \times \text{Pop} \times \text{AF}; \text{where } \text{AF} = (\text{RR}-1)/\text{RR}$$  \hspace{1cm} (3)

$$\Delta \text{HB} = \text{HB}_{LEP15-19} - \text{HB}_{LP20}$$  \hspace{1cm} (4)

$$\text{RR}_{PM2.5} = \exp[\beta_{PM2.5} \times (C_{PM2.5} - C_{PM2.5,0})], \text{ } C_{PM2.5} > 0$$  \hspace{1cm} (5)

$$\text{ER} = \text{RR} - 1$$  \hspace{1cm} (6)

where BM (baseline mortality per 100,000 people of all age groups) was obtained from standardised baseline mortality rates (Table S6) published by the Global Burden of Disease study of 2017 (GBD, 2017). Exposed population (Pop) was estimated by applying a 76.8% factor to the city-wise population of each Indian city. This factor was obtained from the Global Burden of Disease study for India (Balakrishnan et al., 2019), whereby the authors estimated this fraction when the total Indian population was assumed to be exposed to National Ambient Air Quality Standards for PM$_{2.5}$. AF (attributable fraction) of a specific RR (Eq. 5; Table S7) is associated with pollutant load. β is the exposure-response coefficient indicating the additional health risk (such as mortality) caused per unit of PM$_{2.5}$, when concentrations exceed a threshold limit. For example, the β value is considered to be 0.038% for PM$_{2.5}$ per μg m$^{-3}$ (Hu et al., 2015; Shen et al., 2020). $C_{PM2.5}$ is the daily mean PM$_{2.5}$ concentration with reference to the threshold concentration ($C_{PM2.5,0}$ of 0 μg m$^{-3}$), which means that concentrations below or equal to this value are associated with no excess health risk (i.e. RR =1) (Chen et al., 2020).
In the second step, the economic cost was estimated using the value of statistical life (VSL; USD per person) for India. The VSL is based on an individual's valuation of their willingness to pay to reduce the risk of dying, a standard concept used widely (e.g. Xie et al., 2016, Xie et al., 2019, and Etchie et al., 2017) for cost-benefit analyses to reduce air pollution (OECD, 2014; WHO, 2015). The VSL estimate for India is derived from Ghude et al. (2016) as 1.1 million USD per average human lifespan, which is assumed to be the same for the studied period here. The total reduction in HB (per thousand) per city is multiplied by VSL to monetise averted economic cost in billion USD. The value for VSL used in this study is slightly higher than the conservative estimate (USD 602,000) reported by the Organisation for Economic Co-operation and Development for 2010 (OECD, 2014).

The assumptions used for the above analysis were: (1) a uniform RR value is assumed for the city-wise population and did not derive age group and cause-specific RR values for PM$_{2.5}$; (2) state-wise baseline mortality rates are applied to corresponding cities for estimating city-wise HB obtained from the Global Burden of Disease study (GBD, 2017); (3) data from a certain period (25 March to 11 May) is considered to represent lockdown duration and lockdown equivalent periods from previous years (2015-2019), while such analyses are generally conducted with much more comprehensive datasets with an extensive time domain.

3. Results and discussions

3.1. Overview of PM$_{2.5}$ during the lockdown in Indian cities

Table 2 presents the descriptive statistics of five Indian cities during the lockdown period (25 March to 11 May 2020) with respect to similar periods of the past five years, which also allow minimising the impacts of meteorological conditions on temporal characteristics of ambient PM$_{2.5}$ concentrations. The lockdown restrictions reduced the hourly average concentration of PM$_{2.5}$ in all five cities. For example, PM$_{2.5}$ concentrations during lockdown
were 13±10 μg m\(^{-3}\) (Chennai), 40±24 μg m\(^{-3}\) (Delhi), 31±11 μg m\(^{-3}\) (Hyderabad), 29±17 μg m\(^{-3}\) (Kolkata) and 28±11 μg m\(^{-3}\) (Mumbai), which were reduced by 32, 52, 26, 24 and 10% when compared with those of the same period in 2019 in each city, respectively. These improvements varied when compared with different years from 2015 to 2019, ranging from −19 to −43% (Chennai), −41 to −53% (Delhi), −26 to −54% (Hyderabad), −24 to −36% (Kolkata), and −10 to −39% (Mumbai). Most cities showed an improvement from one-fifth to halving their concentrations during the lockdown period. Moreover, the maximum concentration peak in each city decreased appreciably (up to a 5-fold decrease) during the lockdown period when compared against previous years (Table 2).

Delhi consistently exhibited the greatest improvements against previous years because Delhi, compared to other Indian cities, has a higher number of ordinarily on-road vehicles (Table S1), use of which was restricted during the lockdown period. Delhi has three coal-fired thermal power plants in and around it that had no restrictions on their operation during the lockdown period to meet the energy demand of the city. On a relative basis, it is expected that the emissions of power plants may have similarly influenced the PM\(_{2.5}\) concentrations during the lockdown in 2020 and the lockdown-equivalent period in 2019. The source apportionment studies for Delhi suggests the major sources for PM\(_{2.5}\) concentrations to be as secondary aerosols (~21%), soil-dust (~21%), vehicle emissions (~20%), biomass burning (14%), fossil-fuel combustion (~14%), industrial emissions (~6%) and sea-salt (~4%) (Sharma et al., 2016).

While the effect of reduction in traffic emissions during the lockdown is evident (Figure S1), switching-off of the other sources such as fine mineral/soil dust linked to road-traffic and construction activities and industrial emissions that are also the precursor of the secondary aerosol formation may have contributed to the reduced concentrations observed in Delhi. This means that reductions in PM\(_{2.5}\) concentrations during lockdown may also be attributed to reduced levels of co-pollutants such as the NO\(_2\) and SO\(_2\) levels (Table 1), which play an
important role in the formation of secondary aerosols (Chen et al. 2019). Additionally, the effect of the emissions from crop residue burning around Delhi has been often linked with pollution episodes during winters (Kanawade et al., 2020; Hama et al., 2020). The stubble burning of the wheat residue also occurs in surrounding states of Delhi during pre-monsoon season including April and May (Nair et al., 2020), which is also the period of the lockdown considered in this work. However, unlike rice crop residue that is usually not utilised to feed animals and consequently burnt during winters, the wheat crop residue during pre-monsoon season is mostly stocked and utilised to feed domestic animals throughout the year (Kanawade et al., 2020). Moreover, the dispersion conditions during April-May months are expected to be more favourable than the winters to dilute the emissions locally and their limited transport towards the city depending on the pathway of the air mass. While such contributions during the lockdown period in Delhi are expected to be minimal, detailed source apportionment studies coupled with regional scale dispersion modelling are needed to accurately confirm and quantify the contributions of crop residue burning during these months.

It is interesting to note that despite the lockdown, Mumbai recorded the least reductions. Mumbai is a coastal city, and unlike landlocked cities such as Delhi, could even benefit from the flushing of cities emissions by sea breezes (Kumar et al., 2015). Recent source apportionment studies suggest that PM$_{2.5}$ concentrations in Mumbai are dominated by the anthropogenic sources (Police et al., 2018), including crustal material (~9%), sea-salt spray (~6%), coal/biomass combustion (~26%), fuel/oil combustion (~19%), road traffic (~18%) and metal industry (~11%) and the remainder remaining unknown. During the lockdown, coal/biomass burning from the households is expected to even increase further during lockdown when people spend more time indoors while the other sources also expected to remain operational, except the road traffic and metal industry that only makes less than one-
third of total contributions to PM$_{2.5}$ concentrations in Mumbai, possibly explaining a relatively less impact of the lockdown on observed concentrations.

Despite the switch-off of the majority of commercial/industrial and vehicular emission sources (e.g. –79% and ~80% driving in Delhi and Mumbai, respectively, as per Apple mobility trends), which are considered to be dominant sources of emissions in Indian cities (Chen et al., 2020), up to half of the concentration levels remain. This highlights the significance of additional PM$_{2.5}$ sources, such as biomass burning in residential households, roadside waste or municipal solid waste landfills, thermal power plants, electricity generators and regional transport (Kumar et al., 2013; Kumar et al., 2015; Hama et al., 2020), and that holistic source-control measures are needed for improved air quality in post-lockdown environments.

3.1.1 PM$_{2.5}$ frequency analysis

Figure 2 shows the distribution of PM$_{2.5}$ concentrations in different concentration ranges and the peaks during the lockdown, as compared with earlier years in each city, and was carried out by using the GEV model (Eq. 1). Additionally, the frequency histograms of PM$_{2.5}$ concentration during lockdown with the fitted density curve are presented in Figure S2. The PDF of PM$_{2.5}$ concentrations were consistently lower for all cities during the lockdown period, and their shapes are less skewed to the right when compared with the other periods, indicating the expected PM$_{2.5}$ decline due to lockdown restrictions. The extreme PM$_{2.5}$ concentration in the upper tail of the distribution is lower and converges asymptotically to the Gumbel distribution (light tailed). For instance, the GEV model estimated that 1% quantiles of Delhi’s PM$_{2.5}$ concentration in the upper tail were 293 µg m$^{-3}$ in the pre-lockdown periods and 135 µg m$^{-3}$ during lockdown, with a 158 µg m$^{-3}$ difference. It also demonstrates that extreme PM$_{2.5}$ (high concentration) values were less frequent during lockdown in all cities, and particularly in Delhi (Figure 2b). Figure 2f shows a comparison of PM$_{2.5}$ PDF among all five Indian cities.
during lockdown. Delhi experienced the greatest benefit, with a ~53% reduction in PM$_{2.5}$ concentrations and more distributed around the central moment.

In order to understand the behaviour of PM$_{2.5}$, mean variation in the distribution of PM$_{2.5}$ concentrations, and the mean difference in PM$_{2.5}$ concentrations during lockdown, the current lockdown period and relative preceding periods at all cities were compared, as listed in Table 3. Among the cities, Delhi showed the highest percentage reduction in PM$_{2.5}$ concentrations (over 50%) and Mumbai had the lowest at about 12%, with a p-value of <0.01 (1%), which indicates that the percentage of reductions were statistically significant (Table 3). The mean values of PM$_{2.5}$ concentration estimated by the GEV model varied from 20 to 85 μg m$^{-3}$ in the preceding year and 13 to 40 μg m$^{-3}$ during lockdown in Chennai and Delhi, respectively. The percentage reduction for the other cities ranged from 24 to 32%, which were slightly smaller than the measured values for Delhi and Mumbai. The most frequent (mode) value varied from 2 μg m$^{-3}$ (Chennai) to 28 μg m$^{-3}$ (Delhi) during the lockdown period. The most frequent PM$_{2.5}$ concentration ranges in each city during the lockdown period were: 2-6 μg m$^{-3}$ in Chennai, 21-28 μg m$^{-3}$ in Delhi, 24-27 μg m$^{-3}$ in Hyderabad, 17-19 μg m$^{-3}$ in Kolkata and 19-22 μg m$^{-3}$ in Mumbai. Overall, the GEV model is in agreement with observed PM$_{2.5}$ and properly reproduced the distribution of PM$_{2.5}$ during the two study periods.

3.1.2 Temporal and diurnal trends

Figure 3 shows a boxplot for PM$_{2.5}$ during the lockdown period for six years for all cities. To further assess the impact of lockdown on PM$_{2.5}$ trends in five major cities, a smoothed time series of 2020 PM$_{2.5}$ concentrations was compared with that of the previous five years (Figure S3). PM$_{2.5}$ gradually decreased over the lockdown period in all five cities. These observations were more pronounced when the previous five-year average was compared to the lockdown period of 2020 (Figure S3). While all cities showed greater improvements towards
the end of the lockdown period, landlocked cities (Delhi and Hyderabad) reported less than half the PM$_{2.5}$ levels of those of the previous five-year average. Finally, the trend of PM$_{2.5}$ percentage reduction in 2020 compared to the past five years reported similar variations across cities, with fluctuations in the early lockdown period preceding a comparatively steady percentage reduction in PM$_{2.5}$ concentrations as the lockdown continued (Figure S4).

The diurnal variation of PM$_{2.5}$ during the lockdown period was plotted against 2019 (Figure 4) and the previous five years (Figures S5-8) for all cities to show the impact of lockdown on PM$_{2.5}$ levels. Lockdown implementation flattened the diurnal PM$_{2.5}$ concentration trend in all cities (Figure 4). Most of the PM$_{2.5}$ peaks observed during daytime (0600-1800h) were less prominent in 2020 when compared with previous years in all cities, indicating fewer anthropogenic activities as discussed above. The maximum comparative reduction in PM$_{2.5}$ concentrations during lockdown was noted to occur at around 0900h, coinciding with morning traffic peak hours.

In order to further understand PM$_{2.5}$ trends during lockdown, average daily PM$_{2.5}$ concentrations were normalised using average daily PM$_{2.5}$ preceding 23 March 2019 (Figure 4) and the previous years as reference values (Figures S5-8). In all cities except Delhi, PM$_{2.5}$ concentrations gradually reduced during the studied period in all six years when compared to the preceding reference day, and the ratio was further lowered towards the end of study period. In Delhi, however, 2020 PM$_{2.5}$ concentrations were unchanged when compared to preceding reference days (Ratio=1) while higher PM$_{2.5}$ concentrations were recorded in previous, non-lockdown years.

3.2 Lockdown impact on PM$_{2.5}$ across cities

In order to understand the spatial variation of declines in PM$_{2.5}$ concentrations during lockdowns in cities across the world, a review of recent relevant studies was undertaken (Table
S8), visualisation of which is presented in Figures 5 and 6. The Indian cities studied here showed a significant impact of lockdown on air quality. For example, Delhi saw a reduction of up to 52% in average PM$_{2.5}$ concentration when compared with the same time period of the previous year (Table 2). These reductions were expected due to enforced self-isolation and restricted daily activities, with inevitably reduced emissions from traffic and industrial sources (Section 3.1). Our estimated PM$_{2.5}$ reduction was greater for Delhi (-52%) than the -39% reported by Mahato et al. (2020) and -35% by Chauhan and Singh (2020), and was also slightly higher for Mumbai (-14%) than the -10% reported by Chauhan and Singh (2020). This may be attributed to the greater duration of lockdown considered by our study (Table S8). Indeed, other cities across the world, such as Paris (-53%), Amsterdam (-47%) and London (-45%), have shown similarly marked declines in PM$_{2.5}$ concentrations (Shrestha et al., 2020). Kolkata, Hyderabad and Chennai saw 22, 26 and 28% reductions in PM$_{2.5}$ concentrations, respectively. These results are very similar to those for other Asian cities, such as Hunan, Guangdong and Guizhu of China, with PM$_{2.5}$ reductions ranging between 20% and 30% (Table S8). Delhi’s nearly 50% reduction in PM$_{2.5}$ is very similar to results from studies into two other Asian megacities: Shanghai and Beijing (Chauhan and Singh, 2020). In general, relatively large reductions were seen for high-population cities because anthropogenic PM$_{2.5}$ emissions are typically higher in these cities during normal working days than in smaller and less urbanised cities or towns (Zhao et al., 2009).

PM$_{2.5}$ concentration reductions due to lockdown have varied in different cities across the world (Figure 5). Minimal reductions were seen in Rome, where there has been little change in the volume of traffic, a primary source of PM$_{2.5}$ in Rome (Dimitriou and Kassomenos, 2014), and in the city centre of Sao Paulo, where public transportation continued during a partial lockdown (Nakada and Urban, 2020). In China, estimated PM$_{2.5}$ reductions vary from a minimum of 9% in Sichuan to a maximum of 50% in Beijing and Shanghai, due to differences in levels of
urbanisation and in the timing of halts in human activities (Huang et al., 2020a). Meteorology also plays a significant role in pollution dispersion, and rain or storms during the study period may have enhanced dispersion and deposition (Yang et al., 2013). For example, in the US, New York experienced a ~35% reduction, compared with only 4% in Los Angeles, due to rainfall over the lockdown period (Chauhan and Singh, 2020). However, the effect of lockdown on air quality is perceptible in most cities of the world. While the intensity of anthropogenic pollutant sources (discussed in Section 3.1), their switch-off period, lockdown strictness and local meteorological conditions were all influencing factors for variation in the impact of lockdowns on PM$_{2.5}$ across cities (Figure 6), changes in on-road traffic was one clear and major factor. This substantiates our earlier observation (Section 3.1) that decreasing traffic volume showed a proportionally decreasing trend in PM$_{2.5}$ concentrations (Figure S1), explaining why cities with higher vehicular populations tend to show higher reductions in PM$_{2.5}$ concentrations during the lockdown, when transportation activities were restricted.

3.3 Spatial distribution of AOD

We used the AOD index to analyse whether an increase or decrease of aerosol loadings in Indian cities was related to the lockdown. The AOD index at 0.1° pixel or regional scale offers a different perspective regarding the complexity involved in the spatial distribution of aerosol loadings. It also enables visualisation of aerosol hotspots globally, regionally or for a specific city. To do so, we generated 12 AOD maps equally covering the months of March and April of each year from 2015 to 2020 (Figures S9-10). These maps were compared in terms of AOD variation (Section 2.3.2) for all the studied Indian cities.

Figure 7 shows the spatial distribution of AOD over India and across all five cities before and during lockdown (March and April 2020). It is known that AOD is related to topography (Figure 1), with maximum values usually found in lowlands (Dong et al., 2013). We observed a similar pattern in the before-lockdown period and during previous years (Figure 7a-c).
However, as expected, an opposite pattern was seen for the during-lockdown period (Figure 7d), implying a decrease in aerosol loadings in these lowland cities. The spatial distribution of AOD during March 2019, April 2019 and March 2020 is shown in Figure 7a-c, where values in the 0.4-0.8 range can be observed in northern India and 0.6-0.8 in northeast India. Conversely, these values were in the 0.2-0.4 range during April 2020 (Figure 7d) in northern India, with a reduction in aerosol loadings mirroring the lockdown period.

The AOD variations demonstrated an increase or a decrease in aerosol loadings in different regions of India. The AOD variation for March 2020 compared to March 2019 (Figure 8a) shows an increase (20-100%) in aerosol loadings in north India. Conversely, April 2020 (Figure 8b) saw a decrease in north, east and south India, which could be linked to the lockdown. The AOD variation results are in line with those reported by Sharma et al. (2020), who found the highest air quality index (AQI) reductions in north (44%) and south (33%) India and the lowest in central India (15%), where AOD variation showed high spatial-horizontal variation.

AOD variation in five Indian cities during March and April 2020 was compared against that of previous years (Figure 9). When compared to data from 2019, a reduction in aerosol loadings in Hyderabad (5%) and an increase in Mumbai (57%) was observed for the before-lockdown period (March 2020; Figure 9a). These fluctuations in the form of a city-specific decrease or increase could be related to other regional inputs/outputs, such as commercial/industrial emissions and meteorological conditions. It is worth noting that AOD variation can be large and that differences can be complex at regional scale, and the same applies for aerosol properties (Li et al., 2009). Conversely, during lockdown (April 2020), as presented by Figure 9b, a reduction in aerosol loadings was observed for Chennai (29-57%), Delhi (11-29%), Kolkata (2-14%) and Mumbai (1-48%). However, Hyderabad showed fluctuations, with an
increase of 25% in aerosol loadings in April 2020 compared to 2019, and a decrease of 8% with respect to 2018.

The AOD relationship with topography was not seen to continue during the lockdown period, particularly in north India, showing a different pattern to that of previous years (Figure S11). Furthermore, four cities (Chennai, Delhi, Kolkata, and Mumbai) showed an AOD decrease in line with the analysis performed in Section 3.2. However, Hyderabad showed an AOD increase, which is not in line with the reduction discussed in Section 3.2. This variation may be partly related to the different resolution of the dataset involved in this work (e.g. monthly AOD data used here and hourly data used in Section 3.2). Due to the switch-off of most commercial/industrial and vehicular emissions, the AOD increase may also be attributable to other sources related to regional conditions. Some regional sources that may have contributed, include cloud formation around late-afternoon to evening hours, and mineral dust transport (from the Thar Desert) during the pre-monsoon period (March-May) (Kaskaoutis et al., 2009). These topographical and geographical characteristics pointed out that not only anthropogenic but also natural emissions are important sources in this region.

3.4 Averted health burden and associated economic cost

We quantified the health and economic impacts of lockdown-induced reductions in PM$_{2.5}$ concentrations across selected Indian cities (Figure 10 and Table S9). The health impacts are presented in terms of ER and averted HB (i.e. reduced number of premature deaths) associated with daily mean PM$_{2.5}$ exposure during periods with lockdown (HB$_{LP20}$) and without lockdown (HB$_{LEP15-19}$). The mean daily ER reduced by 36.4% over all five cities, with 30, 50, 42, 30 and 30% reductions in Chennai, Delhi, Hyderabad, Mumbai and Kolkata when compared with the previous five years, respectively (Table S9). The reduction in ER during lockdown was greatest for Delhi (20% greater than Chennai, Mumbai and Kolkata, and 8%
greater than Hyderabad) when compared with similar periods of previous years. The mean ER averaged across the five Indian cities (36%) was lower than the 52% value reported by Sharma et al. (2020), who estimated PM-related risk reduction between 16 March and 14 April 2020 by comparing against the same duration in 2017-19 in 22 cities of different regions of India. The reduction in HB during the lockdown, as compared against the lockdown equivalent periods of the previous five years, was greatest for Delhi (49%) and exceeded Chennai, Hyderabad, Mumbai and Kolkata by 19, 8, 19 and 20%, respectively. Combined estimates for all cities indicates that a total of 630 premature deaths have been avoided across five cities during the lockdown period. These estimates of avoided premature deaths due to PM$_{2.5}$ are within the 12% range of the averaged estimate of 5300 (1000 to 11700) for India during the first two weeks of lockdown (February/March 2020) as compared to similar periods of 2017-2019, conducted by Venter et al. (2020). However, these differences may be linked to variations in the considered time domain and number of cities.

The averted HB, using the principle of VSL (Section 2.3.3), is monetised at 0.69 billion USD (Table S9). In other words, during the 2020 lockdown period, India benefited by as much as 0.69 billion USD, which is 14% of India’s total allocated healthcare spending for the fiscal year 2020-2021 (i.e. 5.09 billion USD). This is also roughly 11% higher than India’s planned outlay (USD 622.78 million) towards the environment and climate change as per the Indian Union Budget for the financial year 2020-21 (IBEF, 2020). Additionally, a linear correlation ($R^2 = 0.84$) between changes in prevented premature deaths and the averted economic cost was observed among all cities, which may support the economic value of lockdown restrictions. However, this analysis does not infer or endorse lockdown as a strategy to promote sustainable development but merely highlights the potential health and associated economic co-benefits of reduced business activities and human mobility. The analysis does not account for COVID-19 lockdown impacts on other macroeconomic indicators, such as gross domestic product,
inflation or employment, which might have much more serious and wider implications for the Indian economy (Barua, 2020). In particular, restrictive measures during lockdown have disproportionately affected the livelihood and socio-economic activities of poorer communities (Buheji et al., 2020). Nevertheless, such analyses may contribute towards an understanding of the annual health and economic impacts of lockdown, to support a holistic assessment of impacts and inform relevant policy measures.

4. Conclusions

We studied the impact of the ‘anthropogenic emissions switch-off’ during COVID-19 lockdown on ambient PM$_{2.5}$ in five Indian cities, by comparing 2020 data with that of preceding years and contextualising our results with those from other cities. We also analysed the PDF of PM$_{2.5}$, the spatial distribution of AOD using satellite imagery, and health and economic valuations of the impact of decreased PM$_{2.5}$ concentrations. Conclusions include:

- The analysis of relative reductions in PM$_{2.5}$ due to lockdown restrictions showed the highest (52%) and lowest (10%) reductions for Delhi and Mumbai, respectively, as compared against the same period in 2019. Chennai (32%), Hyderabad (26%), and Kolkata (24%) also showed promising reductions over similar periods. Although the correlation between PM$_{2.5}$ concentrations and the decrease in vehicular traffic across these cities was found to be linear ($R^2 = 0.69$), the potential contribution of commercial/industrial sectors and other PM$_{2.5}$ sources (biomass burning in residential households, thermal power plants, electricity generators, and secondary particle formation) are also considered to be impactful.

- During the lockdown period, extreme PM$_{2.5}$ concentrations were less frequent in all five cities. Delhi benefited the most, with a greater than 50% reduction in concentrations, as also estimated by the GEV model. The GEV model also performed well in capturing the distribution and reproducing the mean percentage reduction in PM$_{2.5}$ for the two study
periods. Statistically significant p-values (<0.01) were observed when comparing PM$_{2.5}$ reductions between the current lockdown period and relative preceding periods in all cities, with Delhi showing the highest concentration reductions (over 50%) and Mumbai the lowest (12%). Therefore, the lockdown period affected PM$_{2.5}$ associated risks by reduction of their onset probability, in particular during peak (day) time.

- During the lockdown period, all five cities displayed a gradual decrease in PM$_{2.5}$ concentrations, resulting in greater improvements towards the end of study duration. Analysis of diurnal variation of PM$_{2.5}$ in these cities revealed that the implementation of lockdown helped to suppress PM$_{2.5}$ peaks during the daytime, and especially in the morning when compared to previous years. Diurnal PM$_{2.5}$ variation showed generally lower concentrations during the lockdown period in 2020 when compared with the same period of previous years.

- Indian cities showed up to 50% reductions (Delhi) in PM$_{2.5}$ concentrations, compared with up to 60% in Europe (Vienna and Zaragoza), and other global cities ranged from 4% in Los Angeles to 42% in Shanghai. The lockdown-induced PM$_{2.5}$ reduction in India was distinct and depended on various factors. Large and densely populated cities with high traffic volumes seemed to correlate with high PM$_{2.5}$ reductions. Other influencing factors included the intensity of other anthropogenic pollutant sources (e.g. indoor), lockdown strictness and duration, and meteorological fluctuations.

- The spatial distribution of AOD during lockdown (April 2020) demonstrated that aerosol loadings decreased in Chennai (29%), Delhi (11%), Kolkata (4%), and Mumbai (1%), with respect to April 2019. AOD variation analysis showed a remarkable reduction in the north, east, and south India, with mitigation related to the switch-off of most commercial/industrial and vehicular emissions. Conversely, central India showed an increase in aerosol loadings and high horizontal spatial variation of AOD, which may be
linked to different sources (e.g. sea aerosol) or the presence of clouds in the area, potentially leading to an overestimation of AOD.

- An appreciable reduction in daily mean PM$_{2.5}$ concentrations due to lockdown led to a decrease in both ER (30-50%) and EV (29-49%) values, which avoided 630 premature deaths across five Indian cities, valued at 0.69 billion USD. While the reduced levels of air pollution during lockdowns indicate clear health and associated economic co-benefits and that the cities should plan more rigorous strategies to control the air pollution, we do not infer or endorse such benefits at the cost of such pandemics that brought devastating impact on communities, businesses, economies, human mobility and so on.

We demonstrated a reduction in PM$_{2.5}$ during the COVID-19 lockdown period in Indian cities, similar to reductions seen in cities elsewhere. A multi-pollutant assessment, considering primary and secondary pollutants over a majority of the lockdown period, is recommended for future work to obtain a holistic picture of the impact of the lockdown period on air pollutants. Generally, cities with larger traffic volumes showed higher reductions in PM$_{2.5}$ during the lockdown. Our study also highlighted that other emissions sources contributed to a permeation in albeit subnormal PM$_{2.5}$ concentrations during the lockdown period. Source apportionment studies, disentangling the contributions of underpinning operational emission sources, are therefore desirable to understand their relative impacts during the ‘anthropogenic emissions switch-off’ of COVID-19 lockdown.

5. **Declaration of interest**

The authors declare no conflict of interest.
CRediT authorship contribution statement

Prashant Kumar: Conceptualization, Funding acquisition, Writing - Original Draft, Resources, Supervision, Project Administration, Methodology, Writing - review & editing.

Sarkawt Hama: Data Curation, Methodology, Writing - Original Draft, Investigation, Validation, Writing - review & editing. Hamid Omidvarborna: Writing - Original Draft, Writing - review & editing. Ashish Sharma: Formal analysis, Writing - review & editing.

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6. References

Ahmadi, M., Sharifi, A., Dorosti, S., Ghousechi, S.J., Ghanbari, N., 2020. Investigation of effective climatology parameters on COVID-19 outbreak in Iran. Science of the Total Environment 729, 138705.

Balakrishnan, K., Dey, S., Gupta, T., Dhaliwal, R.S., Brauer, M., Cohen, A.J., Stanaway, J.D., Beig, G., Joshi, T.K., Aggarwal, S., Sabde, Y., 2019. The impact of air pollution on deaths, disease burden, and life expectancy across the states of India: the Global Burden of Disease Study 2017. The Lancet Planetary Health 3, 26-39.

Bao, R., Zhang, A., 2020. Does lockdown reduce air pollution? Evidence from 44 cities in northern China. Science of the Total Environment 731, 139052.

Barua, S., 2020. Understanding Coronanomics: The Economic Implications of the Coronavirus (COVID-19) Pandemic. SSRN Electronic Journal doi: 10.2139/ssrn.3566477.

Bashir, M.F., Ma, B., Komal, B., Bashir, M.A., Tan, D., Bashir, M., 2020a. Correlation between climate indicators and COVID-19 pandemic in New York, USA. Science of the Total Environment 728, 138835.

Bashir, M.F., Bilal, B.M., Komal, B., 2020b. Correlation between environmental pollution indicators and COVID-19 pandemic: A brief study in Californian context. Environmental Research 187, 109652.

Berman, J.D., Ebisu, K., 2020. Changes in US air pollution during the COVID-19 pandemic. Science of the Total Environment 739, 139864.

Brittain, O.S., Wood, H., Kumar, P., 2020. Prioritising indoor air quality in building design can mitigate future airborne viral outbreaks. Cities & Health. In Press. https://doi.org/10.1080/23748834.2020.1786652

Buheji, M., da Costa Cunha, K., Bekah, G., Mavrić, B., de Souza, Y.L.D.C., da Costa Silva, S.S., Hanafi, M., Yein, T.C., 2020. The Extent of COVID-19 Pandemic Socio-Economic
Impact on Global Poverty. A Global Integrative Multidisciplinary Review. *American Journal of Economics* 10, 213-224.

Carslaw, D.C., Ropkins, K., 2012. openair — an R package for air quality data analysis. *Environmental Modelling & Software* 27-28, 52-61.

Carslaw, D.C., 2015. The openair manual—open-source tools for analysing air pollution data. Manual for version, 1(4). Manual for version 1.1-4, King’s College London.

Chauhan, A., Singh, R.P., 2020. Decline in PM$_{2.5}$ Concentrations over Major Cities Around the World Associated with COVID-19. *Environmental Research* 187, 109634.

Chen, Y., Wild, O., Ryan, E., Sahu, S. K., Lowe, D., Archer-Nicholls, S., Wang, Y., McFiggans, G., Ansari, T., Singh, V., Sokhi, R. S., Archibald, A., Beig, G., 2019. Mitigation of PM$_{2.5}$ and ozone pollution in Delhi: a sensitivity study during the pre-monsoon period. *Atmospheric Chemistry and Physics* 20, 499–514.

Chen, Y., Wild, O., Conibear, L., Ran, L., He, J., Wang, L., Wang, Y., 2020. Local characteristics of and exposure to fine particulate matter (PM$_{2.5}$) in four indian megacities. *Atmospheric Environment X* 5, 100052.

Coccia, M., 2020. Factors determining the diffusion of COVID-19 and suggested strategy to prevent future accelerated viral infectivity similar to COVID. *Science of the Total Environment* 729, 138474.

Coles, S., 2001. An Introduction to Statistical Modeling of Extreme Values, Springer, London, ISBN: 1852334592, 2001.

Collivignarelli, M.C., Abbà, A., Bertanza, G., Pedrazzani, R., Ricciardi, P., Miino, M.C., 2020. Lockdown for COVID-2019 in Milan: What are the effects on air quality? *Science of The Total Environment* 732, 139280.

COVID-19.in, 2020. Government of India, link https://www.mygov.in/covid-19/?cbps=1 (accessed 8 May 2020).
Dantas, G., Siciliano, B., França, B.B., da Silva, C.M., Arbilla, G., 2020. The impact of COVID-19 partial lockdown on the air quality of the city of Rio de Janeiro, Brazil. *Science of the Total Environment* 729, 139085.

dele Jesus, A.L., Thompson, H., Knibbs, L.D., Kowalski, M., Cyrys, J., Niemi, J.V., Kousa, A., Timonen, H., Luoma, K., Petäjä, T., Beddows, D., 2020. Long-term trends in PM$_{2.5}$ mass and particle number concentrations in urban air: The impacts of mitigation measures and extreme events due to changing climates. *Environmental Pollution* 263, 114500.

Dhammapala, R., 2019. Analysis of fine particle pollution data measured at 29 US diplomatic posts worldwide. *Atmospheric Environment* 213, 367-376.

Dimitriou, K., Kassomenos, P., 2014. Indicators reflecting local and transboundary sources of PM$_{2.5}$ and PM$_{COARSE}$ in Rome - Impacts in air quality. *Atmospheric Environment* 96, 154-162.

Dutheil, F., Baker, J.S., Navel, V., 2020. COVID-19 as a factor influencing air pollution? *Environment Pollution* 263, 114466.

Etchie, T.O., Sivanesan, S., Adewuyi, G.O., Krishnamurthi, K., Rao, P.S., Etchie, A.T., Pillarisetty, A., Arora, N.K., Smith, K.R., 2017. The health burden and economic costs averted by ambient PM$_{2.5}$ pollution reductions in Nagpur, India. *Environment International* 102, 145-156.

EPA, 2009. US Environmental Protection Agency. Standard Operating Procedure for the Continuous Measurement of Particulate Matter. https://www3.epa.gov/ttn/amtic/files/ambient/pm25/sop_project/905505_TEOM_SOP_Draft_Final_Sept09.pdf (accessed 17 June 2020).

EPA, 2015. US Environmental Protection Agency. List of designated reference and equivalent methods.https://www3.epa.gov/ttnamti1/files/ambient/criteria/AMTIC%20List%20Dec%202016-2.pdf (accessed 10 May 2020).
Faridi, S., Niazi, S., Sadeghi, K., Naddafi, K., Yavarian, J., Shamsipour, M., Jandaghi, N.Z.S., Sadeghniiat, K., Nabizadeh, R., Yunesian, M., Momeniha, F., 2020. A field indoor air measurement of SARS-CoV-2 in the patient rooms of the largest hospital in Iran. *Science of the Total Environment* 725, 138401.

GBD (2017). Global Burden of Disease Study 2017 (GBD 2017) Data Resources: GHDx. Link http://ghdx.healthdata.org/gbd-2017 (accessed 15 May 2020).

Ghude, S.D., Chate, D.M., Jena, C., Beig, G., Kumar, R., Barth, M.C., Pfister, G.G., Fadnavis, S., Pithani, P., 2016. Premature mortality in India due to PM$_{2.5}$ and ozone exposure. *Geophysical Research Letters* 43, 4650-58.

Guo, H., Kota, S.H., Sahu, S.K., Hu, J., Ying, Q., Gao, A., Zhang, H., 2017. Source apportionment of PM$_{2.5}$ in North India using source-oriented air quality models. *Environmental Pollution* 231, 426-436.

Guo, H., Kota, S.H., Sahu, S.K., Zhang, H., 2019. Contributions of local and regional sources to PM$_{2.5}$ and its health effects in north India. *Atmospheric Environment* 214, 116867.

Hama, S.M., Kumar, P., Harrison, R.M., Bloss, W.J., Khare, M., Mishra, S., Namdeo, A., Sokhi, R., Goodman, P., Sharma, C., 2020. Four-year assessment of ambient particulate matter and trace gases in the Delhi-NCR region of India. *Sustainable Cities and Society* 54, 102003.

Heal, M.R., Kumar, P., Harrison, R.M., 2012. Particles, air quality, policy and health. *Chemical Society Reviews* 41, 6606-30.

Hu, J., Ying, Q., Wang, Y., Zhang, H., 2015. Characterizing multi-pollutant air pollution in China: Comparison of three air quality indices. *Environment International* 84, 17-25.

Huang, X., Ding, A., Gao, J., Zheng, B., Zhou, D., Qi, X., Tang, R., Ren, C., Nie, W., Chi, X., Wang, J., 2020a. Enhanced secondary pollution offset reduction of primary emissions during COVID-19 lockdown in China. EarthArXiv. doi:10.31223/osf.io/hvuzy.
Hyndman, R., Athanasopoulos, G., Bergmeir, C., Caceres, G., Chhay, L., O’Hara-Wild, M., 2019. Forecasting functions for time series and linear models. 2019. https://cran.r-project.org/web/packages/forecast/forecast.pdf (accessed 17 June 2020).

IBEF (2020). Healthcare Industry in India, Indian Healthcare Sector, Services, India Brand Equity Foundation. Link https://www.ibef.org/industry/healthcare-india.aspx (accessed 17 May 2020).

ICMR-PHFI-IHME, 2017. India: Health of the Nation’s States-The India State-level Disease Burden Initiative, Indian Council of Medical Research, Public Health Foundation of India, Institute for Health Metrics and Evaluation, New Delhi (2017). Link: https://www.healthdata.org/sites/default/files/files/policy_report/2017/India_Health_of_the_Nation%27s_States_Report_2017.pdf (accessed 16 May 2020).

Isaifan, R.J. 2020. The dramatic impact of Coronavirus outbreak on air quality: Has it saved as much as it has killed so far? Global Journal of Environmental Science and Management 6, 275-288.

Junger, W.L., De Leon, A.P., 2015. Imputation of missing data in time series for air pollutants. Atmospheric Environment 102, 96-104.

Junninen, H., Niska, H., Tuppurainen, K., Ruuskanen, J., Kolehmainen, M., 2004. Methods for imputation of missing values in air quality data sets. Atmospheric Environment 38, 2895-2907.

Kanawade, V.P., Srivastava, A.K., Ram, K., Asmi, E., Vakkari, V., Soni, V.K., Varaprasad, V., Sarangi, C., 2020. What caused severe air pollution episode of November 2016 in New Delhi?. Atmospheric Environment 222, 117125.

Kanniah, K.D., Zaman, N.A.F.K., Kaskaoutis, D.G., Latif, M.T., 2020. COVID-19's impact on the atmospheric environment in the Southeast Asia region. Science of The Total Environment 736, 139658.
Kaskaoutis, D.G., Badarinath, K.V.S., Kumar Kharol, S., Rani Sharma, A. and Kambezidis, H.D., 2009. Variations in the aerosol optical properties and types over the tropical urban site of Hyderabad, India. *Journal of Geophysical Research: Atmospheres* 114, 22204.

Kerimray, A., Baimatova, N., Ibragimova, O.P., Bukenov, B., Kenessov, B., Plotitsyn, P., Karaca, F., 2020. Assessing air quality changes in large cities during COVID-19 lockdowns: The impacts of traffic-free urban conditions in Almaty, Kazakhstan. *Science of the Total Environment* 730, 139179.

Kim, M., Zhang, X., Holt, J.B., Liu, Y., 2013. Spatio-temporal variations in the associations between hourly PM$_{2.5}$ and aerosol optical depth (AOD) from MODIS sensors on Terra and Aqua. *Health* 5, 8-13.

Kotnala, G., Mandal, T.K., Sharma, S.K., Kotnala, R.K., 2020. Emergence of blue sky over Delhi due to Coronavirus disease (COVID-19) lockdown implications. *Aerosol Science and Engineering*, 1-11. [https://doi.org/10.1007/s41810-020-00062-6](https://doi.org/10.1007/s41810-020-00062-6)

Kumar, P., Jain, S., Gurjar, B.R., Sharma, P., Khare, M., Morawska, L., Britter, R., 2013. New directions: Can a “Blue Sky” return to Indian megacities? *Atmospheric Environment* 71, 198-201.

Kumar, P., Khare, M., Harrison, R.M., Bloss, W.J., Lewis, A., Coe, H., Morawska, L., 2015. New directions: Air pollution challenges for developing megacities like Delhi. *Atmospheric Environment* 122, 657-661.

Kumar, P., Gulia, S., Harrison, R.M. and Khare, M., 2017. The influence of odd–even car trial on fine and coarse particles in Delhi. *Environmental Pollution* 225, 20-30.

Kumar, P., Morawska, L., 2019. Could Fighting Airborne Transmission be the Next Line of Defence against COVID-19 Spread? City Environ. Interactions. In Press, [https://doi.org/10.1016/j.cacint.2020.100033](https://doi.org/10.1016/j.cacint.2020.100033).

Lal, P., Kumar, A., Kumar, S., Kumari, S., Saikia, P., Dayanandan, A., Adhikari, D., Khan,
M.L., 2020. The dark cloud with a silver lining: Assessing the impact of the SARS COVID-19 pandemic on the global environment. *Science of The Total Environment* 732, 139297.

Li, Y., Qian, H., Hang, J., Chen, X., Hong, L., Liang, P., Li, J., Xiao, S., Wei, J., Liu, L., Kang, M., 2020a. Evidence for probable aerosol transmission of SARS-CoV-2 in a poorly ventilated restaurant. medRxiv, 2020.2004.2016.20067728.

Li, L., Li, Q., Huang, L., Wang, Q., Zhu, A., Xu, J., Liu, Z., Li, H., Shi, L., Li, R., Azari, M., 2020b. 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. *Science of The Total Environment* 732, 139282.

Li, Z., Zhao, X., Kahn, R., Mishchenko, M., Remer, L., Lee, K.H., Wang, M., Laszlo, I., Nakajima, T., Maring, H., 2009. Uncertainties in satellite remote sensing of aerosols and impact on monitoring its long-term trend: a review and perspective. *Annals of Geophysics* 27, 2755-2770.

Liu, J., Li, Z., 2014. Estimation of cloud condensation nuclei concentration from aerosol optical quantities: influential factors and uncertainties. *Atmospheric Chemistry & Physics* 14, 471-483.

Liu, Y., Ning, Z., Chen, Y., Guo, M., Liu, Y., Gali, N.K., Sun, L., Duan, Y., Cai, J., Westerdahl, D., Liu, X., 2020. Aerodynamic analysis of SARS-CoV-2 in two Wuhan hospitals. *Nature*, 1-6.

Mahato, S., Pal, S., Ghosh, K.G., 2020. Effect of lockdown amid COVID-19 pandemic on air quality of the megacity Delhi, India. *Science of The Total Environment* 730, 139086.

Mandal, I., Pal, S., 2020. COVID-19 pandemic persuaded lockdown effects on environment over stone quarrying and crushing areas. *Science of The Total Environment* 732, 139281.

Martini, F.M.S., Hasenkopf, C.A., Roberts, D.C., 2015. Statistical analysis of PM$_{2.5}$...
observations from diplomatic facilities in China. *Atmospheric Environment* 110, 174-185.

Martins, L.D., Wikuats, C.F.H., Capucim, M.N., de Almeida, D.S., da Costa, S.C., Albuquerque, T., Carvalho, V.S.B., de Freitas, E.D., de Fátima Andrade, M., Martins, J.A., 2017. Extreme value analysis of air pollution data and their comparison between two large urban regions of South America. *Weather and Climate Extremes* 18, 44-54.

Mitra, A., Chaudhuri, T.R., Mitra, A., Pramanick, P., Zaman, S., Mitra, A., Chaudhuri, T.R., Mitra, A., Pramanick, P., Zaman, S., 2020. Impact of COVID-19 related shutdown on atmospheric carbon dioxide level in the city of Kolkata. *Science and Education* 6, 84-92.

Morawska, L., Cao, J., 2020. Airborne transmission of SARS-CoV-2: The world should face the reality. *Environment International* 139, 105730.

Muhammad, S., Long, X., Salman, M., 2020. COVID-19 pandemic and environmental pollution: A blessing in disguise?. *Science of The Total Environment* 728, 138820.

Mukherjee, A., Agrawal, M., 2018. Air pollutant levels are 12 times higher than guidelines in Varanasi, India. Sources and transfer. *Environmental Chemistry Letters* 16, 1009-16.

Nair, M.M., Bherwani, H., Kumar, S., Gulia, S., Goyal, S.K., Kumar, R., 2020. Assessment of contribution of agricultural residue burning on air quality of Delhi using remote sensing and modelling tools. *Atmospheric Environment* 230, 117504.

Nakada, L.Y.K., Urban, R.C., 2020. COVID-19 pandemic: Impacts on the air quality during the partial lockdown in São Paulo state, Brazil. *Science of The Total Environment* 730, 139087.

NASA, 2020a. Aerosol Optical Depth. Link https://earthobservatory.nasa.gov/global-maps/MODAL2_M_AER_OD (accessed 11 May 2020).

NASA, 2020b. MODIS DATA - Moderate Resolution Imaging Spectroradiometer. Link https://nsidc.org/data/modis/terra_aqua_differences (accessed 11 May 2020).

OECD (2014). The cost of air pollution: health impacts of road transport, OECD Publishing.
doi: 10.1787/9789264210448-en.

Otmani, A., Benchrif, A., Tahri, M., Bounakhla, M., El Bouch, M., Krombi, M.H., 2020. Impact of COVID-19 lockdown on PM$_{10}$, SO$_2$ and NO$_2$ concentrations in Salé City (Morocco). *Science of The Total Environment* 735, 139541.

Ottosen, T.B., Kumar, P., 2019. Outlier detection and gap filling methodologies for low-cost air quality measurements. *Environmental Science: Processes & Impacts* 21, 701-713.

Pacione, M., 2006. Mumbai. *Cities*, 23, 229–238.

Paital, B., 2020. Nurture to nature via COVID-19, a self-regenerating environmental strategy of environment in global context. *Science of The Total Environment* 729, 139088.

PIB, 2020. Ministry of Health and Family Welfare, Update on Novel Coronavirus. Link https://pib.gov.in/pressreleaseiframepage.aspx?prid=1601095 (accessed 8 May 2020).

Police, S., Sahu, S.K., Tiwari, M., Pandit, G.G., 2018. Chemical composition and source apportionment of PM$_{2.5}$ and PM$_{2.5-10}$ in Trombay (Mumbai, India), a coastal industrial area. *Particuology* 37, 143-153.

R Core Team, 2020, A language and environment for statistical computing R Foundation for statistical computing, Vienna, Austria (2020).

Saadat, S., Rawtani, D., Hussain, C.M., 2020. Environmental perspective of COVID-19. *Science of The Total Environment* 728, 138870.

Saez, M., Tobias, A., Varga, D. and Barceló, M.A., 2020. Effectiveness of the measures to flatten the epidemic curve of COVID-19. The case of Spain. *Science of The Total Environment* 727, 138761.

Sahu, S.K., Kota, S.H., 2016. Significance of PM$_{2.5}$ air quality at the Indian capital. *Aerosol and Air Quality Research* 17, 588-597.

Şahin, M., 2020. Impact of weather on COVID-19 pandemic in Turkey. *Science of The Total Environment* 728, 138810.
Schiermeier, Q., 2020. Why pollution is plummeting in some cities - but not others. Nature News (9 April 2020). Link https://tinyurl.com/NatureNewsCOVID-19 (accessed 10 May 2020).

Scroll, 2019. Delhi is world’s most polluted city; Kolkata, Mumbai also in top 10, says global air quality monitor. Link https://scroll.in/latest/943917/delhi-is-worlds-most-polluted-city-kolkata-mumbai-also-in-top-10-says-global-air-quality-monitor (accessed on 14 May 2020)

Setti, L., Passarinì, F., De Gennaro, G., Baribieri, P., Perrone, M.G., Borelli, M., Palmisani, J., Di Gilio, A., Torboli, V., Pallavicini, A., Ruscio, M., 2020. SARS-CoV-2 RNA found on particulate matter of Bergamo in Northern Italy: First preliminary evidence. medRxiv.

Sharma, S.K., Mandal, T.K., Jain, S., Sharma, A., Saxena, M., 2016. Source apportionment of PM$_{2.5}$ in Delhi, India using PMF model. Bulletin of Environmental Contamination and Toxicology 97, 286-293.

Sharma, A.K., Balyan, P., 2020. Air pollution and COVID-19: Is the connect worth its weight?. Indian Journal of Public Health 64, 132-134.

Sharma, S., Zhang, M., Gao, J., Zhang, H. and Kota, S.H., 2020. Effect of restricted emissions during COVID-19 on air quality in India. Science of The Total Environment 728, 138878.

Shen, F., Zhang, L., Jiang, L., Tang, M., Gai, X., Chen, M., Ge, X., 2020. Temporal variations of six ambient criteria air pollutants from 2015 to 2018, their spatial distributions, health risks and relationships with socioeconomic factors during 2018 in China. Environment International 137, 105556.

Shi, X., Brasseur, G.P., 2020. The response in air quality to the reduction of Chinese economic activities during the COVID-19 outbreak. Geophysical Research Letters 47, e2020GL088070.
Shrestha, A.M., Shrestha, U.B., Sharma, R., Bhattarai, S., Tran, H.N.T. and Rupakheti, M., 2020. Lockdown caused by COVID-19 pandemic reduces air pollution in cities worldwide. EarthArXiv. doi:10.31223/osf.io/edt4j.

Shukla, K., Kumar, P., Mann, G.S., Khare, M., 2020. Mapping spatial distribution of particulate matter using Kriging and Inverse Distance Weighting at supersites of megacity Delhi. *Sustainable Cities and Society* 54, 101997.

Sicard, P., De Marco, A., Agathokleous, E., Feng, Z., Xu, X., Paoletti, E., Rodriguez, J.J.D., Calatayud, V., 2020. Amplified ozone pollution in cities during the COVID-19 lockdown. *Science of The Total Environment* 735, 139542.

Srivastava, S., Kumar, A., Baudhik, K., Gautam, A.S., Kumar, S., 2020. 21-Day lockdown in India dramatically reduced air pollution indices in Lucknow and New Delhi, India. *Bulletin of Environmental Contamination and Toxicology*, 1-9. https://doi.org/10.1007/s00128-020-02895-w

SSEC, 2020a. Terra Orbit Tracks. Link: https://www.ssec.wisc.edu/datacenter/terra/GLOBAL.html (accessed 11 May 2020).

SSEC, 2020b. Aqua Orbit Tracks. Link: https://www.ssec.wisc.edu/datacenter/aqua/GLOBAL.html (accessed 11 May 2020).

Tobías, A., Carnerero, C., Reche, C., Massagué, J., Via, M., Minguillón, M.C., Alastuey, A., Querol, X., 2020. Changes in air quality during the lockdown in Barcelona (Spain) one month into the SARS-CoV-2 epidemic. *Science of The Total Environment* 726, 138540.

Tomar, A., Gupta, N., 2020. Prediction for the spread of COVID-19 in India and effectiveness of preventive measures. *Science of The Total Environment* 728, 138762.

Venter, Z.S., Aunan, K., Chowdhury, S., Lelieveld, J., 2020. COVID-19 lockdowns cause global air pollution declines with implications for public health risk. medRxiv. DOI: https://doi.org/10.1101/2020.04.10.20060673.
Wang, Y., Chen, Y., 2019. Significant climate impact of highly hygroscopic atmospheric aerosols in Delhi, India. *Geophysical Research Letters* 46, 5535-5545.

Wang, P., Chen, K., Zhu, S., Wang, P. and Zhang, H., 2020a. Severe air pollution events not avoided by reduced anthropogenic activities during COVID-19 outbreak. *Resources, Conservation & Recycling* 158, 104814.

Wang, Y., Yuan, Y., Wang, Q., Liu, C., Zhi, Q., Cao, J., 2020b. Changes in air quality related to the control of coronavirus in China: Implications for traffic and industrial emissions. *Science of The Total Environment* 731, 139133.

Wang, Q., Su, M., 2020. A preliminary assessment of the impact of COVID-19 on environment – A case study of China. *Science of The Total Environment* 728, 138915.

Wei, X., Chang, N.B., Bai, K., Gao, W., 2019. Satellite remote sensing of aerosol optical depth: advances, challenges, and perspectives. *Critical Reviews in Environmental Science and Technology* 50, 1-86.

WHO, (2015). Economic cost of the health impact of air pollution in Europe *Clean air, health and wealth*. Link [http://www.euro.who.int/pubrequest](http://www.euro.who.int/pubrequest) (accessed 12 May 2020).

WHO, 2016. Global Urban Ambient Air Pollution Database. Link: [https://www.who.int/airpollution/data/who-aap-database-may2016.xlsx?ua=1](https://www.who.int/airpollution/data/who-aap-database-may2016.xlsx?ua=1) (accessed 9 May 2020).

WHO, 2020a. WHO announces COVID-19 outbreak a pandemic. Link: [http://www.euro.who.int/en/health-topics/health-emergencies/coronavirus-covid-19/news/news/2020/3/who-announces-covid-19-outbreak-a-pandemic](http://www.euro.who.int/en/health-topics/health-emergencies/coronavirus-covid-19/news/news/2020/3/who-announces-covid-19-outbreak-a-pandemic) (accessed 8 May 2020).

WHO, 2020b. WHO Coronavirus disease (COVID-19) dashboard. Link: [https://covid19.who.int/](https://covid19.who.int/) (accessed 21 May 2020).

Wu, J.T., Leung, K., Bushman, M., Kishore, N., Niehus, R., de Salazar, P.M., Cowling, B.J.,
Lipsitch, M., Leung, G.M., 2020a. Estimating clinical severity of COVID-19 from the transmission dynamics in Wuhan, China. Nature Medicine 26, 506-510.

Wu, X., Nethery, R.C., Sabath, B.M., Braun, D., Dominici, F., 2020b. Exposure to air pollution and COVID-19 mortality in the United States: A nationwide cross-sectional study. medRxiv, 2020.2004.2005.20054502.

Yang, X., Yao, Z., Li, Z., Fan, T., 2013. Heavy air pollution suppresses summer thunderstorms in central China. Journal of Atmospheric and Solar-Terrestrial Physics 95, 28-40.

Xie, Y., Dai, H., Dong, H., Hanaoka, T., Masui, T., 2016. Economic impacts from PM$_{2.5}$ pollution-related health effects in China: a provincial-level analysis. Environmental Science & Technology 50, 4836-43.

Xie, Y., Dai, H., Zhang, Y., Wu, Y., Hanaoka, T., Masui, T., 2019. Comparison of health and economic impacts of PM$_{2.5}$ and ozone pollution in China. Environment International 130, 104881.

Zambrano-Monserrate, M.A., Ruano, M.A., Sanchez-Alcalde, L., 2020. Indirect effects of COVID-19 on the environment. Science of the Total Environment 728, 138813.

Zhao, X., Zhang, X., Xu, X., Xu, J., Meng, W., Pu, W., 2009. Seasonal and diurnal variations of ambient PM$_{2.5}$ concentration in urban and rural environments in Beijing. Atmospheric Environment 43, 2893-2900.
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Figure 1. Topographic map of India, showing the locations, population density and vehicle population in Chennai, Delhi, Hyderabad, Kolkata and Mumbai. The references to the human and vehicle population and data used in the figure above are available in Table S1.
Figure 2. Density plot of hourly PM$_{2.5}$ concentration before and during lockdown for (a) Chennai, (b) Delhi, (c) Hyderabad (d) Kolkata, (e) Mumbai, and (f) all cities only during the lockdown period.
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**Table 1.** Summary of recent studies on COVID-19 and air quality impacts.

| Study area (city, country) | Key findings                                                                                                                                                                                                                                                                                                                                                                                                                                                                 | Author (year)                                                                                      |
|----------------------------|-----------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|-----------------------------------------------------------------------------------------------------|
| India (Delhi, Mumbai, Kolkata and Bangalore) | ● Assessed overall impact of social and travel lockdown in five megacities of India and evaluated spatiotemporal variations in five criteria pollutants over two time periods, i.e., March-April 2019 and March-April 2020 and 10th-20th March 2020 (before lockdown) and 25th March to 6th April 2020 (during lockdown).  
  ● Statistically significant reduction was found in all megacities for all pollutants except for O₃ with concentration declines in PM₂.₅ (~41%) PM₁₀ (52%), NO₂ (51%) and CO (28%) during the lockdown phase in Delhi when compared to before lockdown. Similar reductions were observed for other megacities. | Jain and Sharma (2020)                                                                 |
| India (Delhi) | ● Analysed PM₁₀, PM₂.₅, SO₂, NO₂, CO, O₃ and NH₃ over 34 monitoring stations in Delhi during pre-lockdown periods and during the lockdown.  
  ● Air quality significantly improved during lockdown, with reductions of 60% (PM₁₀), 39% (PM₂.₅), 53% (NO₂) and 30% (CO) compared to 2019. | Mahato et al. (2020)                                                                 |
| India (Kolkata) | ● Measured atmospheric CO₂ levels with a portable CO₂ analyzer at 12 sites during April 2019 (pre-lockdown) and April 2020 (post-lockdown).  
  ● 30-40% decrease in CO₂ levels with significant temporal variation was observed (p < 0.01), but no statistically significant variation was observed between sites. | Mitra et al. (2020)                                                                 |
| India (22 cities in different regions) | ● Examined impact of lockdown measures on criteria pollutant (PM₁₀, PM₂.₅, CO, NO₂, O₃ and SO₂) concentration reductions and analysed data between 16 March to 14 April from 2017 to 2020.  
  ● Compared to previous years (2017-2019), during lockdown periods, reductions in concentrations were up to 43% (PM₂.₅), 31% (PM₁₀), ~52% (mean excessive PM risks), 10% (CO), and 18% (NO₂), while an increase of 17% in O₃ and negligible changes in SO₂ were detected. Reductions in AQI were up to 44% (North), 33% (South), 29% (East), 15% (Central) and 32% (West) India. | Sharma et al. (2020)                                                                 |
| India | ● Based on data-driven estimation methods and curve fitting, a 30-day projection of the effectiveness of preventive measures (social isolation and lockdown) on the spread of COVID-19 in India was developed.  
  ● Authors highlighted that the proposed method well estimated and predicted the positive cases and number of recovered cases within a certain range and will be a beneficial tool for policymakers and health officials. | Tomar and Gupta (2020)                                                                 |
| Location          | Analysis                                                                                      | Reference          |
|-------------------|-----------------------------------------------------------------------------------------------|--------------------|
| Brazil (São Paulo)| ● Assessed impacts of partial lockdown in São Paulo on concentration levels of CO, NO, NO₂, and O₃.  
● CO, NO, NO₂, and O₃ concentrations reduced by 65, 77, 54 and 30%, respectively, during the lockdown period. | Nakada and Urban (2020) |
| China             | ● Data from the TROPOspheric Monitoring Instrument (TROPOMI) sensor on-board ESA’s Sentinel-5 satellite showed reductions in NO₂ concentrations due to lockdown near Wuhan, China (~30%) and worldwide.  
● CO₂ also decreased by 25% in China and by 6% worldwide. Fatalities might have decreased due to reduced air pollution levels. | Dutheil et al. (2020) |
| China             | ● Daily mortality due to air pollution and COVID-19 between Dec 2019 and Mar 11th 2020 showed huge differences, indicating that lockdown likely saved more lives by preventing ambient air pollution than by preventing infection.  
● NASA satellite images showed reductions of up to 30% in NO₂ levels and about 25% carbon emissions (~100 Mt equivalent to 6% of the global emissions) over the same period in Feb 2020 due to quarantine. | Isaifan (2020) |
| China (330 cities) and USA (New York) | ● Evaluated the significance of environmental (including air quality) impacts of the COVID-19 lockdown in 330 Chinese cities and New York (USA).  
● When compared with 2019 data, air quality in 2020 improved by 11% across 330 cities of China and 50% in New York (USA). | Saadat et al. (2020) |
| China             | ● Investigated impact of reduced anthropogenic activities due to lockdown on air pollution using simulation with the community multi-scale air quality model between 01 Jan and 12 Feb 2020 and compared three air pollution scenarios.  
● Decreased PM₂.₅ in Beijing, Shanghai, Guangzhou, and Wuhan by 9.23, 6.37, 5.35, and 30.79 μg m⁻³, respectively. However, reduction ratios of PM₂.₅ concentrations were smaller than those of precursor emissions, partially due to unfavorable meteorological conditions. | Wang et al. (2020a) |
| China             | ● Assessed the dynamic environmental (including air quality) impacts of COVID-19 in China during the period of Jan-Mar 2020 compared to 2019.  
● Reduction in CO₂ emissions by >25% ~ 1M tonne of C or 6% of global emissions over two weeks (spring festival 2020 and 2019). Satellite data: decline in NO₂ (~30% China; 50% Wuhan). Air-pollutant monitoring in 337 major cities (Jan-Mar 2020): Decline in PM₂.₅ (14.8%), NO₂ (25%), CO (6.2%), PM₁₀ (20.5%), SO₂ (21.4%); no change in O₃.  
● Reduced economic activities decrease energy consumption and hence environmental pollution. | Wang and Su (2020) |
| China and Europe (France, Germany, ...) | ● Studied positive and negative impacts of the COVID-19 lockdown on the environment in severely affected areas. | Zambrano-Monserrat et al. (2020) |
| Location                              | Details                                                                                                                                                                                                 | Reference(s) |
|--------------------------------------|--------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|--------------|
| Spain, and Italy)                    | Countries such as China, USA, Italy and Spain.                                                                                                                                                           |              |
|                                      | ● Quarantine led to reduced air pollutant concentrations in: (i) China, for NO$_2$ (12.9 to 22.8 µg m$^{-3}$, Wuhan) and PM$_{2.5}$ (18.9 µg m$^{-3}$ in 367 cities (Wuhan-1.4 µg m$^{-3}$)) ~ 20-30% between the monthly average for February 2020 against monthly averages for last three years (February 2017-2019); and (ii) Europe (Rome, Madrid, and Paris), in NO$_2$ and PM$_{2.5}$ concentrations in February 2020 compared to previous three years (2017-2019). |              |
| China (120 cities)                   | ● Using generalised additive models, the authors explored relationships between ambient air pollutant (PM$_{2.5}$, PM$_{10}$, SO$_2$, CO, NO$_2$ and O$_3$) concentrations and COVID-19 infection, utilising associations between meteorological variables (temperature, wind speed, RH) and daily COVID-19 confirmed cases.  
● Significant positive correlations were found between pollutant concentrations (PM$_{2.5}$, PM$_{10}$, NO$_2$ and O$_3$) and newly COVID-19 confirmed cases. For example, a 10 µg m$^{-3}$ increase in PM$_{2.5}$, PM$_{10}$, NO$_2$, and O$_3$ was linked to a 2.24%, 1.76%, 6.94%, and 4.76% increase in daily counts of confirmed cases, respectively. Conversely, a 10-µg m$^{-3}$ increase in SO$_2$ was linked to a 7.79% decrease in COVID-19 confirmed cases. | Zhu et al. (2020) |
| New York, Los Angeles, Zaragoza, Rome, Dubai, Delhi, Mumbai, Beijing and Shanghai | ● Dec 2019-Mar 2020 (COVID-19 outbreak period) compared with 2017-2019 for changes in PM$_{2.5}$ concentration (data from USEPA)  
● Decline in PM$_{2.5}$ concentration in March 2020 compared to March 2019 in: Dubai (11%), Rome (no change), Delhi (35%), Mumbai (14%), Beijing (50%), Shanghai (50%), New York (32%), Los Angeles (4%). No change in Zaragoza. | Chauhan and Singh (2020) |
| China, Spain, France, Italy, USA     | ● Study compiled environmental data released by NASA and ESA (European Space Agency) before and after the pandemic (Jan-Mar, 2019 and 2020) and discussed its impact on environmental quality  
● Found reductions in NO$_2$ levels of up to 20-30% in Wuhan (China), Spain, France, Italy and the USA. | Muhammad et al. (2020) |
| Global                              | ● Studied the impact of weather variables and air pollution (CO$_2$, NO$_2$, PM) on the global infection and spreading rate of COVID-19.  
● Air pollution was linked to an increased risk of COVID-19 infection and, therefore, strict and early lockdown measures (particularly in India and China) led to significant reductions in concentrations of NO$_2$ and CO$_2$ and this was observed across many metropolitan cities globally. | Paith (2020) |
| Global (27 countries, China, India and Europe) | ● Using satellite data and a network of more than 10,000 air quality stations, the authors investigated whether or not reduced air pollution levels during Feb-Mar 2020 were related to COVID-19 lockdown events.  
● 7,400 (340 to 14,600) premature deaths and 6,600 (4,900 to 7,900) pediatric asthma cases were avoided | Venter et al. (2020) |
over two weeks post-lockdown. PM$_{2.5}$-related avoided premature mortality was estimated for China as 1,400 (1,100 to 1,700) and for India as 5,300 (1000 to 11,700). Globally, 0.78 (0.09 to 1.5) million premature deaths and 1.6 (0.8 to 2) million pediatric asthma cases could be avoided in 2020, assuming the lockdown-induced reduction in concentrations is maintained throughout the year.

| Iran (Tehran, Mazandaran, Alborz, Gilan, and Qom) | Examined the influence of several parameters on COVID-19 spread. Parameters included weather variables (e.g. average temperature, average precipitation, humidity, wind speed, and average solar radiation), number of COVID-19 infected people, population density, intra-provincial movement, and infection days.  
- Population density and intra-provincial movement showed a direct correlation with the infection outbreak, while regions with comparatively low wind speed, humidity and solar radiation exposure showed higher rates of infection due to favourable conditions for virus survival.  
Ahmadi et al. (2020) |
| Iran | Air samples from 2-5m of patients’ beds were collected to measure airborne transmission of COVID-19.  
- All tests results were negative, with no positive readings within 2m distance of patients.  
Faridi et al. (2020) |
| Italy (Brescia, Lodi, Monza, Alessandria, Milan, Turin, Padua, Bergamo and Cremona, Rovigo and Genoa, Lombardy region) | Determined associations between infected people and environmental, demographic and geographical factors governing transmission dynamics of COVID-19.  
- Cities with more than 100 days of air pollution (i.e. surpassing PM$_{10}$ or O$_3$ limits) showed significantly higher average numbers of infected individuals (~3,600 infected individuals on 7 April 2020) than in cities with less than 100 days of air pollution (~1000 infected individuals).  
Coccia (2020) |
| Spain (National) | Using generalised linear mixed models, the authors estimated the shape of the epidemic curve of accumulated cases and evaluated the effect of the intervention introduced by the Spanish government to mitigate the COVID-19 epidemic.  
- After one day of implementation of the measures, the variation rate of accumulated cases was reported to reduce daily on average from 3.1 to 5.1%. However, until 14 March 2020, the introduced measures to reduce the epidemic curve of COVID-19 have not reached the planned phase.  
Saez et al. (2020) |
| Spain (Barcelona) | Investigated changes in air pollution levels during the lockdown in terms of urban background and traffic air quality observed stations.  
- After two weeks of lockdown, the authors found a substantial reduction in BC (-45%) and NO$_2$ (-51%), mostly related to traffic emissions. PM$_{10}$ also decreased from -28 to -31%, whereas levels of O$_3$ increased from +33% to +57%.  
Tobias et al. (2020) |
| Location | Description | References |
|----------|-------------|------------|
| Turkey (Nine cities: Istanbul, Izmir, Ankara, Konya, Kocaeli, Sakarya, Isparta, Bursa and Adana, Turkey) | • Studied the impact of meteorological variables (temperature, dew point temperature, humidity, and wind speed) on the COVID-19 pandemic over four periods (1, 3, 7, and 14 days).  
• Population, wind speed 14 days ago, and temperature on the day showed the highest correlations, respectively. | Şahin (2020) |
| USA (New York) | • Investigated correlations between climate indicators (average temperature, minimum temperature, maximum temperature, rainfall, average humidity, wind speed, and air quality) and the COVID-19 pandemic.  
• Meteorological variables (average temperature, minimum temperature) and air quality showed strong correlation with the COVID-19 pandemic. | Bashir et al. (2020) |
| USA (Nationwide) | • Investigated associations between long-term average exposure to PM$_{2.5}$ and increased risk of COVID-19 death in the United States.  
• Found that an increase of $1 \mu g m^{-3}$ in PM$_{2.5}$ is associated with an 8% increase in the COVID-19 death rate (95% CI 2% to 15%) | Wu et al. (2020b) |
| Malaysia and Southeast Asia | • Investigated air quality impact of lockdown. Decrease in AOD (Singapore, Brunei, Malaysia and the Philippines), tropospheric NO$_2$ column density (27-34% in most countries except for Ho Chi Minh and Yangon cities) was noted. AODs remained very high (up to 2) in northern Southeast Asia due to extensive forest fires and agricultural burning.  
• In Malaysia (March-April 2020), decrease in AOD (urban area: 40-70%), PM$_{10}$ (industrial: 28–39%, urban: 26–31%), PM$_{2.5}$ (industrial: 20–42%, urban: 23–32%), NO$_2$ (industrial: 33–46%, urban: 63-64%), SO$_2$ (urban: 9-20%), and CO (urban: 25-31%) compared with 2018 and 2019 was noted. | Kanniah et al. (2020) |
| Southern European cities (Nice, Rome, Valencia and Turin) and Wuhan (China) | • Presented the challenge of reducing the formation of secondary pollutants such as O$_3$ even with lockdown’s reduced emission. In comparison to 2017-19, O$_3$ increased (24% in Nice, 14% in Rome, 27% in Turin, 2.4% in Valencia and 36% in Wuhan) due to reduced NOx and lower O$_3$ titration by NO, while reductions were observed in NO$_2$ (~53% in Europe and 57% in Wuhan), NO (~63% in Europe), and PM$_{2.5}$ and PM$_{10}$ (~8% in Europe and ~42% in Wuhan) at urban stations. NO$_2$ and NO decreased by ~65% and ~78% respectively at traffic stations in Europe.  
• Last years’ weekend comparison showed that NOx was ~ 49% lower in all cities, O$_3$ was ~10% higher in Southern Europe and 38% higher in Wuhan, PM was similar (~6%) in Southern Europe. | Sicard et al. (2020) |
| Yangtze River Delta Region (China) | • The WRF-CAMx modelling system and monitoring data were applied to investigate the impact of lockdown on air quality and sources of residual pollution for future air pollution control. | Li et al. (2020b) |
- Reductions in SO$_2$ (16–26%), NOx (29–47%), PM$_{2.5}$ (27–46%) and VOCs (37–57%) emissions were observed. Declines in PM$_{2.5}$ (31.8%, 33.2%), NO$_2$ (45.1%, 27.2%) and SO$_2$ (20.4%, 7.6%) were observed during the two periods of lockdown compared to 2019, however ozone increased greatly. Though primary emissions reduced (15%–61%), PM$_{2.5}$ varied little (15-79 μg m$^{-3}$), suggesting high background and residual pollution.
- Source apportionment pointed to industry (32.2–61.1%), mobile (3.9–8.1%), dust (2.6–7.7%), and residential (2.1–28.5%) sources of PM$_{2.5}$ and a 14.0–28.6% contribution of long-range transport from northern China.

| 44 cities in northern China | Estimated the effects of COVID-19-related travel restrictions on air pollution. The AQI decreased by 7.80%, and SO$_2$, PM$_{2.5}$, PM$_{10}$, NO$_2$, and CO decreased by 6.76%, 5.93%, 13.66%, 24.67%, and 4.58% respectively. Human movements were reduced by 69.85%, partially causing reduction in the AQI, PM$_{2.5}$, and CO, while completely mediating SO$_2$, PM$_{10}$, and NO$_2$ reductions. |
|----------------------------|--------------------------------------------------------------------------------|
| Almaty (Kazakhstan)        | Analysed the effects of COVID-19-lockdown on air pollutants. Reductions in PM$_{2.5}$ (21%, spatial variations: 6–34%), CO (49%) and NO$_2$ (35%) were observed compared to 2018–2019, whereas O$_3$ increased by 15% compared to 17 days before the lockdown. Benzene and toluene were 2–3 times higher than for 2015–2019. Pointed towards non-traffic-related sources, such as coal-fired combined heat and power plants, household heating systems, garbage burning and bathhouses. |
| Delhi (India)              | Assessed pollutant datasets and observed a significant improvement in ambient air quality due to lockdown. NOx reduced by ~14 times the peak value (342 to 24 ppb from 12 January to 30 March 2020). Significant reduction in the PM$_{10}$, PM$_{2.5}$, NH$_3$, SO$_2$, NO, NO$_2$, NOx and CO concentrations. |
| Review (Global)            | Reviewed the evidence for SARS-CoV-2 transmission by particulate matter pollutants. PM$_{2.5}$ was suggested to transmit coronavirus via aerosols in Italy and Wuhan. PM$_{2.5}$ may have direct correlation with virus transmission and related mortality. |
| Lucknow and New Delhi (India) | Analysed primary air pollutant data before and after lockdown (21-days). Significant decline in PM$_{2.5}$, NO$_2$ and CO was seen in both cities, with less significant decline in SO$_2$. Perceptible air pollution mitigation was due to adoption short and periodic lockdowns. |
### Northern China
- Quantified surface PM$_{2.5}$, NO$_2$, CO, and SO$_2$ reductions during the lockdown.
- PM$_{2.5}$ and NO$_2$ decreased by 29 ± 22% and 53 ± 10%, respectively, but O$_3$ increased by a factor 2.0 ± 0.7. Similar reductions (PM$_{2.5}$: 31 ± 6%, NO$_2$: 54 ± 7%) and increase (O$_3$: 2.2 ± 0.2 fold) were noted in the urban area of Wuhan.
- Shi and Brasseur (2020)

### Rio de Janeiro (Brazil)
- Discussed the partial lockdown impact on city air quality, comparing 2019 and weeks prior to the virus outbreak.
- CO, related to light-duty vehicular emissions, reduced to 30.3–48.5%. Due to industrial and diesel input, NO$_2$ decreased to a lower extent and PM$_{10}$ reduced only during the first week. O$_3$ increased due to the decrease in nitrogen oxide levels in a VOC-controlled scenario.
- In April, vehicular flux and people movement increased due to public disregard of lockdown. Compared to 2019, NO$_2$ and CO median values were 24.1–32.9 and 37.0–43.6% lower. Meteorological interferences (e.g. transport of industrial pollutants) might have also impacted the results.
- Dantas et al. (2020)

### Global
- Tested the hypothesis of improved environmental quality due to lockdown induced atmospheric pollutants reduction.
- COVID-19 cases in the tropical regions were relatively lower than the European and American regions. Reductions in NO$_2$ (Substantial: 0.00002 mol m$^{-2}$), CO (low: <0.03 mol m$^{-2}$) and AOD (low-to-moderate: ~0.1–0.2) were observed in the major hotspots of COVID-19 outbreak during Feb–Mar 2020. High hazard was projected in major areas of the globe (absolute humidity: 4–9 g m$^{-3}$) during Apr–Jul 2020. The northern hemisphere may be more susceptible in May–Jul 2020 while tropical regions in Oct–Nov 2020.
- Scope for restoring the global environment from the ill-effects of anthropogenic activities through temporary shutdown measures was suggested.
- Lal et al. (2020)

### California (USA)
- Employed Spearman and Kendall correlation tests to analyse the association of PM$_{2.5}$, PM$_{10}$, SO$_2$, NO$_2$, Pb, VOC, and CO with COVID-19 cases.
- PM$_{10}$, PM$_{2.5}$, SO$_2$, NO$_2$, and CO had significant correlation with the COVID-19 epidemic and adoption of green environmental policies was promoted to shield human life.
- Bashir et al. (2020b)

### Northern China
- Evaluated AQI, PM$_{2.5}$, PM$_{10}$, CO, SO$_2$, NO$_2$, and O$_3$ changes during the COVID-19 control period. The AQI decreased from 89.6 to 71.6. 322 out of 366 cities experienced AQI decline. All pollutants decreased except O$_3$ because of less scavenging of HO$_2$ due to lower fine particle loadings. Reductions in NO$_2$, PM$_{2.5}$, CO, and SO$_2$ were linked to reduced activities of transportation, secondary industries and industrial sector respectively.
- Wang et al. (2020b)
| Location | Summary |
|----------|---------|
| Milan (Italy) | Importance of reactions between gaseous and particulate pollutants, and control of residential emissions were illustrated. Lowering both NOx and VOCs will be needed to control O3. Assessed the effect of partial and total lockdown on air quality in meteorologically comparable periods. A significant reduction of PM$_{10}$, PM$_{2.5}$, BC, benzene, CO and NOx was observed mainly due to reduced vehicular traffic. SO$_2$ also dropped but remained unchanged in the adjacent areas. O3 increased due to the minor NO concentration and was more accentuated in the adjacent areas with reduced concentrations of benzene. | Collivignarelli et al. (2020) |
| Salé City (Morocco) | Analysed air pollutants before and during the lockdown period. PM$_{10}$, SO$_2$ and NO$_2$ concentrations were reduced respectively by 75%, 49% and 96%. The three-dimensional air mass backward trajectories, using the HYSPLIT model, demonstrated that long-range transported aerosol contributions out-balanced the reductions in locally emitted PM$_{10}$. Differences in the air mass back trajectories and the meteorology between these two periods were shown. | Otmani et al. (2020) |
| Dwarka river basin within Jharkhand and West Bengal (India) | Explored the impact of forced lockdown on PM$_{10}$, land surface temperature, river water quality and noise using image- and field-derived data. PM$_{10}$ concentration reduced from 189-278 μg m$^{-3}$ in the pre-lockdown period to 50-60 μg m$^{-3}$ after 18 days of lockdown in selected four stone crushing clusters. | Mandal and Pal (2020) |
Table 2. Overview of summary statistics of hourly PM$_{2.5}$ concentration for five cities during lockdown period (25 March to 11 May 2020) for each year. $n$ is the number of hourly averaged concentration data points for the above-noted duration after cleaning the data (Section 2.3). We estimated p-value using t-tests based on the hourly PM$_{2.5}$ dataset for each year and they were found to be statistically significant (p-value <0.0001).

| Cities   | Year | 2020     | 2019     | 2018     | 2017     | 2016     | 2015     |
|----------|------|----------|----------|----------|----------|----------|----------|
|          | Mean±SD | 13±10   | 19±13    | 16±12    | 23±10    | 19±11    | 19±12    |
|          | Med (max) | 11 (95) | 17 (79)  | 13 (370) | 22 (63)  | 17 (165) | 16 (80)  |
|          | $n$       | 1084    | 1095     | 1104     | 1063     | 909      | 923      |
|          | ΔC \(^1\) (%) | -32     | -19      | -43      | -32      | -32      | -32      |
| Delhi    | Mean±SD | 40±24   | 84±54    | 71±43    | 84±57    | 85±79    | 68±45    |
|          | Med (max) | 34 (195) | 71 (519) | 63 (286) | 67 (470) | 62 (865) | 55 (395) |
|          | $n$       | 1152    | 1150     | 1145     | 1068     | 1150     | 1144     |
|          | ΔC (%)     | -52     | -44      | -52      | -53      | -41      |
| Hyderabad| Mean±SD | 31±11   | 42±17    | 54±19    | 68±26    | 52±24    | 53±22    |
|          | Med (max) | 30 (106) | 39 (137) | 50 (206) | 62 (207) | 49 (228) | 48 (222) |
|          | $n$       | 1142    | 1142     | 1066     | 1017     | 1123     | 907      |
|          | ΔC (%)     | -26     | -43      | -54      | -40      | -42      |
| Kolkata  | Mean±SD | 29±17   | 38±16    | 43±16    | 45±13    | 42±15    | 38±19    |
|          | Med (max) | 25 (107) | 36 (115) | 40 (138) | 44 (172) | 39 (102) | 34 (129) |
|          | $n$       | 1151    | 1149     | 1031     | 1075     | 1121     | 1125     |
|          | ΔC (%)     | -24     | -33      | -36      | -31      | -24      |
| Mumbai   | Mean±SD | 28±11   | 31±16    | 44±22    | 46±25    | 34±19    | 44±26    |
|          | Med (max) | 26 (74)  | 28 (118) | 39 (195) | 39 (165) | 30 (217) | 38 (377) |
|          | $n$       | 1044    | 1141     | 947      | 980      | 977      | 1092     |
|          | ΔC (%)     | -10     | -36      | -39      | -18      | -36      |

\(^1\)ΔC = [(C_{2020} - C_{201x})/C_{201x}] \times 100 is the percent change of average PM$_{2.5}$ in 2020 against the previous years.
Table 3. Sample and GEV model estimated means, percentage of mean reduction in PM$_{2.5}$ and p-values before (2019) and during lockdown periods.

| City     | 25 March to 11 May 2019 | 25 March to 11 May 2020 |
|----------|-------------------------|-------------------------|
|          | Sample mean (μg m$^{-3}$) | GEV estimated mean (μg m$^{-3}$) | Sample mean (μg m$^{-3}$) | GEV estimated mean (μg m$^{-3}$) | % of mean reduction (2019-2020) | p-value      |
| Chennai  | 20                      | 13                      | 32                      | 2.2e-16                     |
| Delhi    | 84                      | 40                      | 53                      | 2.2e-16                     |
| Hyderabad| 42                      | 31                      | 26                      | 2.2e-16                     |
| Kolkata  | 38                      | 29                      | 24                      | 2.2e-16                     |
| Mumbai   | 31                      | 28                      | 12                      | 1.5e-09                     |