Air quality change due to COVID-19 lockdown in India and its perception by public

Abinaya Sekar  
National Institute of Technology Calicut  https://orcid.org/0000-0002-0096-4980

Jasna R S  
National Institute of Technology Calicut  https://orcid.org/0000-0001-9662-1722

Binoy B V  
National Institute of Technology Calicut  https://orcid.org/0000-0002-6397-1096

Prem Mohan  
National Institute of Technology Calicut  https://orcid.org/0000-0002-8897-1340

George Kuttiparichel Varghese  (✉ gkv@nitc.ac.in)  
National Institute of Technology Calicut  https://orcid.org/0000-0002-5327-2697

Research Article

Keywords: Air quality, Perceived Air Quality, COVID-19, Lockdown, Odds ratio, Air Quality Index

DOI: https://doi.org/10.21203/rs.3.rs-74610/v1

License: ☑️ ☐️ This work is licensed under a Creative Commons Attribution 4.0 International License.  
Read Full License
Abstract

In this study, air quality data for 100 days recorded at 193 stations distributed throughout India were analyzed to understand the changes in air quality following the country-wide lockdown imposed from 25th March to 17th May 2020 to contain the spread of the COVID-19 pandemic. The responses from a nationwide online survey conducted to obtain public perceptions of air quality improvement were also analyzed. On average, an approximately 40% improvement in the air quality index was observed, contributed by a reduction in 40% of PM$_{10}$, 44% of PM$_{2.5}$, 51% of NO$_2$ and 21% of SO$_2$. There was a significant difference between the levels of all the pollutants before and after the lockdown (p<0.05), except ozone. The Pearson correlation coefficient showed that the correlation between PM$_{10}$ and PM$_{2.5}$ with ozone was significant after the lockdown period, indicating that a significant portion of the particulates present in the atmosphere after the lockdown period is secondary. The survey for public perception showed that 60% of the 1750 respondents perceived improvement in air quality. On a scale of 1 to 5, the respondents from Delhi perceived the highest improvement, from 2.2 to 4.5. An odds ratio of 17 indicated a very high dependence of perception on actual air quality. PM$_{10}$ levels had the highest influence in shaping public perceptions of air quality. The results from Google Trends analysis showed that media had no influence on shaping the perception of improvement in air quality.

Introduction

Pollution has become the major environmental cause of many diseases and premature deaths worldwide (Landrigan et al. 2017). The escalated levels of air pollution can be attributed mainly to rapid strides in industrialization and increased vehicular traffic. Other sources of air pollution include burning fossil fuels such as coal, wood and dry grass and construction activities (Gurjar et al. 2016). The Central Pollution Control Board (CPCB) of India identifies 17 different categories of industries in the country, viz., aluminum/copper/zinc smelters, thermal power plants, integrated iron and steel plants, petrochemical industries, caustic soda plants, cement plants, oil refineries, distilleries, dye and dye intermediate manufacturers, tanneries, drug and pharmaceutical industries, pulp and paper mills, sugar factories, pesticide manufacturing units and fertilizer plants. The air pollutants emitted from these numerous industries include ambient particulate matter (PM) of various sizes, metals, gases, and many organic compounds. More than 200 million vehicles (MORTH 2019) on roads also contribute significantly to air pollution in India. It is estimated that the emissions from the transport sector account for almost 56% and 70%, respectively, of the total PM$_{2.5}$ and PM$_{10}$ load in the air environment of the country. Of the total PM$_{2.5}$ contribution from the sector, 70% is from diesel-operated vehicles (Guttikunda et al. 2019).

Exposure to air pollutants triggers asthma, wheezing, rhinitis, eczema (Norbäck et al. 2019) and allergic disease (Brandt et al. 2015). Additionally, changes in several neurobehavioral functions in children and evidence of depression and cognitive impairment in the elderly have been found as after-effects of continuous exposure to polluted air (Costa et al. 2020). Studies have indicated that poor outdoor and
indoor air quality increases mortality in some of the major cities in India (Nagpure et al. 2014; Lelieveld et al. 2015). Largely, air quality is associated with human activities. However, it is impossible to restrict human activities to affect improvements in air quality, although nonessential activities can be restricted to a certain extent (Bao and Zhang 2020). However, there can be instances when even essential activities are restricted as a response to unusual situations.

At the end of 2019, a novel infectious disease was reported in Wuhan, China (Huang et al. 2020). Later, this pandemic was identified as from the corona virus family and was named COVID-19 (Chen et al., 2020). WHO confirmed the transmission of COVID-19 through respiratory droplets among humans (WHO, 2020). The corona virus outbreak became an international crisis with its spread to many countries, resulting in the deaths of many and interruption of normal life. Nationwide lockdowns had to be implemented in most of the affected countries to contain the spread of the disease. The first confirmed case of COVID-19 infection in India was reported from the state of Kerala on 30 January 2020. The country observed a jump in corona virus cases by the 4th of March. On 22 March 2020, a 14-hour voluntary public curfew was imposed in India, followed by lockdowns in some districts as well as major cities where COVID-19 positive cases were identified. The Prime Minister of India ordered a nationwide lockdown for 21 days with effect from 25th March 2020 (Ministry of Home Affairs 2020). This was further extended up to the 3rd of May, with some conditional relaxations in areas where limited cases were reported. Even after these restrictions, the number of COVID-19 positive cases was on the rise, and a third phase of lockdown was implemented up to 17th May. Several countries across the world went into lockdown due to the tremendous increase in the number of positive cases and the deaths associated with it. As a result of the series of lockdowns in India, industrial activities, transportation by all modes, and almost all other polluting activities decreased drastically. This had a positive impact on the environment, with pollution levels falling significantly in most cities of India (Mahato et al. 2020; Sharma et al. 2020). The same trends were reported in many other countries of the world, such as China (Bao and Zhang 2020; Muhammad et al. 2020; Wang et al. 2020b; Zambrano-monserrate et al. 2020; Zhang et al. 2020), Italy (Cristina et al. 2020; Muhammad et al. 2020; Zambrano-monserrate et al. 2020), Spain, France (Muhammad et al. 2020; Zambrano-monserrate et al. 2020), USA (Muhammad et al. 2020), Germany (Zambrano-monserrate et al. 2020), Brazil (Dantas et al. 2020), Kazakhstan (Kerimray et al. 2020), etc.

The negative impact of COVID 19 was felt in the industrial, trade and commercial sectors of the country (ICRA 2020a, b, c). It is expected that the country will go into the worst recession in recent times along with most other countries of the world. Perhaps the only area where the shutdown had a positive impact was the air environment. The shutdown resulted in the drastic reduction of pollutants discharged into the air environment.

Several studies have shown the influence of the economic activities of a society on its air quality. NASA and the European Space Agency recently reported that there is a reduction in nitrogen-dioxide (NO₂) levels in China after the economic slowdown following complete lockdown of the country associated with COVID-19 infections (NASA Earth observatory 2020). A similar effect was observed in history earlier
during the collapse of the Soviet Union in 1991. There was a significant reduction in greenhouse gases attributed to the reduction in meat consumption following the economic slowdown (Schierhorn et al. 2019). A study from California showed that economic indicators had a statistically significant effect on air pollution levels (Davis 2012). Similarly, a study conducted in New Jersey showed that economic activity levels can be used as a potential marker for assessing exposure to traffic-related pollutants in the absence of monitoring data (Davis et al. 2010).

The reduced traffic and restricted industrial activities have probably resulted in the reduction in PM$_{2.5}$, carbon monoxide (CO) and NO$_2$ concentrations reported from different countries of the world during COVID-19-induced lockdown. The control on construction-related activities could also have contributed to the decrement observed in PM$_{2.5}$ and PM$_{10}$ concentrations. The decrease in ambient sulfur-di-oxide (SO$_2$) concentration during the control period was proportional to the decreased emission from industrial activities (Dantas et al. 2020; Mahato et al. 2020; Wang et al. 2020b). Although there was a decrease in air pollution in many countries of the world during lockdown, restricted anthropogenic activities were not sufficient alone to explain the reduction in the level of pollutants in air. A study from China reported that due to the partial effect of unfavorable meteorological conditions, the reduction ratios of PM$_{2.5}$ concentrations, as a result of lockdown, were smaller than the reduction ratios of precursor emissions (Wang et al. 2020a), indicating the influence of weather on ambient pollutant concentrations. Even though the major air pollutants, such as PM$_{2.5}$, PM$_{10}$, CO, NO$_2$, SO$_2$ and ammonia (NH$_3$), saw a large reduction in their concentrations, the concentration of ozone (O$_3$) increased during the lockdown period in many parts of the world (Cristina et al. 2020; Dantas et al. 2020; Mahato et al. 2020; Wang et al. 2020b). The reason behind this reverse trend of O$_3$ concentration was identified as the decreased PM concentrations. Reduced PM in air results in increased photochemical activities and thus higher O$_3$ production by giving way for more sunlight to pass through the atmosphere (Dang and Liao 2017; Li et al. 2018). This may also be due to the favorable conditions for ozone formation, such as high temperatures and solar radiation indices (Escudero et al. 2019; Dantas et al. 2020). The decrease in NOx concentration in the atmosphere (Monks et al. 2015) and reduced utilization of O$_3$ by NO were also probably the reasons behind the increase in O$_3$ concentrations (Gorai et al. 2017) during the control period. This also shows that meteorological conditions are an important parameter. The simultaneous control of PM$_{2.5}$ and O$_3$ is quite difficult, and it requires measures such as proper adjustment of industrial structure and energy structure (Zhang et al. 2020). A study from China found that the largest decrease in concentration during the COVID-19 lockdown period was for NO$_2$ and the least decrease was for SO$_2$ (Wang et al. 2020b).

There are many advantages for the public's perception of pollution being strongly correlated to actual levels of pollution. On the one hand, it prevents people from taking unnecessary health risks and generates public opinion against polluting emissions, forcing regulatory agencies to take corrective measures. On the other hand, it allows industries to judiciously make use of the assimilative capacity of the environment, resulting in net economic benefits to society. However, there are various factors other
than the actual levels of pollution that shape the perception of pollution. The perception of air quality has been found to be correlated with factors such as gender, education, age, health status, resident area, etc. (Guo et al. 2016; Oltra and Sala 2016). Howe et al. (2003) reported that aged responders had a more negative perception of pollution than younger responders, attributable, possibly, to their bad environmental experience during their younger ages. In another study, subjects older than 40 years, living in an urban area, having a college-level education and poor child health conditions perceived the air quality around the area as worse (Guo et al. 2016). The gender of the subjects considered was found to be associated with perception by Elliott et al. (1999). They found that most of the women reported that poor air quality will lead to adverse health effects compared to the men respondents. The respondents with respiratory indications (nocturnal shortness of breath, phlegm, rhinitis, etc.) reported higher levels of annoyance for degraded air quality (Sunyer et al. 2007). Factors such as health status, smoking status, and exposure time were also reported to have a significant impact on air quality perception (Pantavou et al. 2018).

However, in general, there is a strong correlation between perceived and actual air quality, although the perception varies with respect to age, gender, residence type, education, income, health condition and indoor house environment (Guo et al. 2016). Residents living in the proximity of industries and heavy traffic regions had negative perceptions of the air quality and health risks associated with it (Howel et al. 2003; Brody et al. 2004; Kohlhuber et al. 2006). Nikolopoulou et al. (2009) observed a good correlation between perceived air quality and PM concentrations in the study area. As the PM concentration increased, there was an increase in the number of ‘poor air quality’ votes and a decrease in the number of ‘good air quality’ votes. In another study, the public could truly perceive the most influencing factors in a neighborhood’s air quality (Mally 2016).

As far as human health is concerned, proper perception of pollution has significant advantages. Studies have shown that perceived air pollution and perceived health risk play a prominent role in the manifestation of health symptoms and contribute to ailments (Lloyd et al. 2005; Brosschot et al. 2006). In many cases, these health symptoms act as protective mechanisms against the severe consequences of pollution (Engen 1991). Often, the sources of pollutants may be identified based on olfactory sensations (pleasant or unpleasant). If the source is perceived to be unpleasant, it is more likely to have a negative impact on human health (Sucker et al. 2008). In addition to the olfactory systems, the trigeminal sensory system, which is activated by both vaporous substances and particles, also plays an important role in such perceptions. The sensation generated by trigeminal chemoreception includes pungency and irritation, where the reflex action prevents the inhalation of hazardous substances. The warning features of this defense reflex include sweating, coughing, mucus release, tearing and salivary flow (Silver 1991).

Perception studies on air quality have a significant role in creating awareness among people on the importance of having clean air (Evans et al. 1988; Liu et al. 2017). It was found that a significant proportion of the population was ready to take actions for the reduction of air pollution, as they perceived the air quality to be poor (Semenza et al. 2008; Li et al. 2016). Perception studies have been useful in providing suggestions to the government for improving air quality (Lan et al. 2016; Li et al. 2016). Wang
et al. (2015) found that 90% of the respondents from Shanghai, China agreed that air quality improvement is the responsibility of government and the individual citizens of the country.

In the context of the importance of public perception in air pollution management, this study analyzes the change in air quality following the COVID-19 lockdown in India and its perception by the general public. Extensive data on actual air quality from 193 monitoring stations covering the whole country were taken from the repository of the regulatory agency. The public perception of air quality was obtained through an online questionnaire survey conducted among the general public answered by 1750 respondents. The data obtained were analyzed to obtain quantitative estimates of improvements in air quality and the relationship between actual and perceived air quality. The analysis results were used to arrive at conclusions regarding factors that were most influential in shaping perception.

Methodology

Air quality data

Geographic and demographic diversity is perhaps the most striking feature of India, the second most populous country in the world. From the Himalayan Mountains in the north to the Kanyakumari cape in the south and from the Thar Desert and salt marshes of the west to the humid forests of the northeast, the Indian main land covers an area of 3,278,982 sq.km. The tropic of cancer divides the country roughly into two equal halves. The southern part of the country, being a peninsula, experiences milder variations in temperature, whereas the northern region experiences extremes in temperature (R.B. Singh 2016).

Currently, there are approximately 231 continuous air monitoring stations in the country. These are connected to the web-based system, and the data are open to access for the public (CPCB 2020a). These monitoring stations are maintained by the respective state pollution control boards. Considering the size of the country, the number of air quality monitoring stations is insufficient. The government has plans to strengthen the network in major cities in a phased manner (CPCB 2020b). For this study, the air quality data for a total of 100 days (from 7-02-2020 to 16-05-2020) recorded at 193 air quality monitoring stations were downloaded from the Central Pollution Control Board (CPCB) website (https://app.cpcbccr.com/ccr/#/caaqm-dashboard-all/caaqm-landing). The pollutants considered in this study include PM$_{10}$, PM$_{2.5}$, SO$_2$, NO$_2$ and O$_3$. Furthermore, the air quality index (AQI), as calculated by CPCB, was also considered in this study (CPCB 2014). The period from 7-02-2020 to 22-03-2020 is considered the pre-lockdown period, and the period from 23-03-2020 to 16-05-2020 is considered the lockdown period in this study. The collected data were subjected to analysis for 1) changes in the concentration of air pollutants with respect to different zones/states, 2) the number of days the pollution level exceeded the
permissible levels before and during lockdown, and 3) changes in the pollution level before and during lockdown with respect to the type of locality (residential, traffic and industrial) and major cities (based on the population). The type of locality was decided based on the location of the monitoring station, whether in residential areas with minimum traffic, near major roads and traffic intersections or in industrial areas.

**Multivariate statistical analysis was conducted using** Pearson’s correlation coefficients. The correlation coefficient is often used to determine the extent of the relationship between the variables when it is compared in pairs. There are various types of correlation coefficients (Núñez-Alonso et al. 2019), in which Pearson’s correlation is the most commonly used method in linear regression. In this study, it is used to measure the strength of the relationship between the selected pollutants before and after the lockdown period.

**GIS analysis**

To estimate the spatial variation of air quality across the country, interpolation of the air quality data from monitoring stations was carried out. The most commonly used interpolation techniques for air pollution studies include inverse distance weighting (IDW), kriging and splining (Kumar Jha et al. 2011). Of this, kriging is a powerful statistical tool where the interpolated values are modeled by a Gaussian process governed by prior covariances. The mathematical equation used in the ArcGIS platform is shown in equation (1) (Environmental Systems Research Institute 2016).

\[
Z^*(S_0) = \sum_{i=1}^{N} \lambda_i Z(S_i) \quad (1)
\]

where,

- \(Z^*(S_0)\) - value at the predicted location
- \(Z(S_i)\) - measured value at the \(i^{th}\) location
- \(\lambda_i\) - unknown weight for the value measured at the \(i^{th}\) location (this value depends on the distance to the location predicted and the spatial relationships among the measured values around the predicted location)
- \(N\) - number of the measured values

**Perception Survey**
Residents from all across the country were asked to complete the questionnaire (n=1750). The survey was conducted between 17-4-2020 and 27-5-2020. A total of 16 survey questions were asked. The entire survey was divided into three sections: 1) location details, 2) perception of improvement of air quality, visibility, health effects and sources, and 3) willingness to maintain air quality. Survey questions in sections 2 and 3 were asked on the rating scale and Likert scale. For example,

“Rate the air quality in your locality before the lock-down period?” 1= Poor to 5= Good.

“Is there improvement in visibility in your locality?” No improvement, Slight improvement, Moderate improvement, Significant improvement and Don’t know.

“I will actively be involved in maintaining the current status of the environment” Strongly agree, Agree, Undecided, Disagree and Strongly Disagree.

The questionnaire for the online survey is generated and circulated through Google forms (included as supplementary material). The questionnaire had the option of collecting the Geolocations of responders with their permission for plotting the results easily in ArcGIS. All statistical analyses were performed using SPSS 2.0. Descriptive statistics were used to present the respondents’ demographics and the response to the questionnaire. Independent sample non-parametric tests were conducted to understand the difference in opinion of the respondents belonging to different categories. Test of significance was performed using Chi-square ($\chi^2$) and t-tests. Statistical significance was considered at $p<0.05$. The strength of the relationship between the two variables was determined using “Effect size”, calculated with Cramer’s V (Sullivan and Feinn 2012).

The perceptions were analyzed based on 1) location (rural or urban), 2) type of locality (residential, near traffic junctions, near industries and near hospitals), 3) different zonal councils (western zonal council (W), southern zonal council (S), northern zonal council (N), eastern zonal council (E) and central zonal council (C), and 4) major cities (selected based on the population and pollution levels). Zonal councils in India were set up vide Part-III of the States Re-organizations Act, 1956, and this classification was made to establish advisory council “to develop the habit of cooperative working” among the states in the council. Councils were created to develop healthy inter-state and Center-state relationships by solving the inter-state issues and balancing the socio-economic development of the corresponding zones (Government of India 2019).
The perception of air quality is often influenced by the media (Murukutla et al. 2019). To find the effect of media on air quality perception, an analysis was conducted using “Google trends”. Keywords such as “Air Quality”, “Air Quality Index” “AQI” and “Air Pollution” were used to analyze the frequency of discussions on air quality by the media. Frequent discussions on the topic by media may unduly affect the perception.

**Qualitative response analysis**

The question asked in the qualitative survey part is “Please give your suggestions for maintaining the air quality after the lock-down period”. Qualitative response analysis was conducted by the process of identification, examination and finally interpreting the frequently repeated keywords in the textual data and based on the frequency of repetition of the keywords. Based on this analysis, suggestions are given to maintain the air quality after the lockdown period.

**Relationship between AAQ and PAQ**

The perception of air quality was collected on a rating scale from 1 to 5. Similarly, the AQI and the concentrations of the individual pollutants were also converted to rating scales as per breakpoint scales proposed by CPCB (CPCB 2014) given in Table 1. Both values were subjected to a test of significance using SPSS 2.0 to establish the relationship between PAQ and AAQ.

| AQI Category                  | PM$_{10}$ 24 hr | PM$_{2.5}$ 24 hr | NO$_2$ 24 hr | SO$_2$ 24 hr | O$_3$ 8 hr | Rating scale |
|-------------------------------|----------------|-----------------|--------------|--------------|------------|--------------|
| Good (0-50)                   | 0-50           | 0-30            | 0-40         | 0-40         | 0-50       | 5            |
| Satisfactory (51-100)         | 51-100         | 31-60           | 41-80        | 41-80        | 51-100     | 4            |
| Moderately Polluted (101-250) | 101-250        | 61-90           | 81-180       | 81-380       | 101-168    | 3            |
| Poor (201-300)                | 251-350        | 91-120          | 181-280      | 381-800      | 169-208    | 2            |
| Very Poor & Severe (301-400) & | 351-430 & 430 + | 121-250 & 250 + | 280-400 & 400 + | 801-1600 & 1600 + | 748 + | 1 |
The responses of people from two states, one where there was significant improvement in air quality (Delhi) and the other with nominal improvement in air quality (Telangana), were used to calculate the odds ratio. The odds ratio was calculated as in equation (2):

\[
OR = \frac{N_{pi}/N_{ni}}{N_{pn}/N_{nn}} \quad (2)
\]

where,

- \(N_{pi}\) Number of people who perceived significant improvement in air quality from an area (Delhi) where there was significant improvement in actual air quality
- \(N_{ni}\) Number of people who perceived no/slight improvement in air quality from an area (Delhi) where there was significant improvement in actual air quality
- \(N_{pn}\) Number of people who perceived significant improvement in air quality from an area (Telangana) where there was only nominal improvement in actual air quality
- \(N_{nn}\) Number of people who perceived no/slight improvement in air quality from an area (Telangana) where there was only nominal improvement in actual air quality

When OR is >1, it indicates that the perception is dependent on improvement in the air quality. The higher the value of OR, the stronger the dependence.

**Results And Discussion**

**Actual Air Quality**

The overall country averages for PM\(_{10}\) calculated using the interpolated values were 116 \(\mu g/m^3\) and 70 \(\mu g/m^3\) before and after lockdown, respectively. Statistical analysis using a t-test showed that there was a significant difference in PM\(_{10}\) levels before and after lockdown, with \(p<0.05\). **Fig 1(a-c)** shows PM\(_{10}\) levels before and after lockdown and improvement in its levels during lockdown. The overall country averages calculated using the interpolated value for PM\(_{2.5}\) are 56 \(\mu g/m^3\) and 31 \(\mu g/m^3\) before and after lockdown, respectively. Statistical analysis using a t-test showed that there was a significant difference in PM\(_{2.5}\) levels before and after lockdown,
Fig 1(d-f) shows PM$_{2.5}$ levels before and after lockdown and improvement in its levels during lockdown. Compared to other states in India, many of the southern states had low PM$_{10}$ and PM$_{2.5}$ levels before and after the lockdown period. However, while considering the improvement in air quality in absolute terms following lockdown, the southern states showed lower improvement compared to the other states. Though the improvement in absolute terms was less, an overall better air quality was observed in the southern states. With respect to the percentage improvement in air quality calculated with the actual data of PM$_{2.5}$ and PM$_{10}$, West Bengal showed the highest (64%) improvement in air quality. Orissa showed the lowest improvement in air quality (10%) with respect to PM$_{2.5}$ levels. In the case of Haryana, Uttar Pradesh and Bihar, the percentage reduction of PM$_{2.5}$ was found to be higher than the percentage reduction of PM$_{10}$. The values of PM$_{2.5}$/PM$_{10}$ were found to be > 0.5 in North East states such as Arunachal Pradesh and Meghalaya, which shows that a major portion of PM$_{10}$ was PM$_{2.5}$. The North East states are less industrialized and scarcely populated, and this observation points to the long-distance transport of PM$_{2.5}$ from other places. The country-wide average reduction percentages for PM$_{10}$ (44%) and PM$_{2.5}$ (51%) were significantly different (p<0.05), with PM$_{2.5}$ having a higher reduction.

The overall country averages using the interpolated value for NO$_2$ were 30.45 µg/m$^3$ and 14.64 µg/m$^3$ before and after lockdown, respectively. Statistical analysis using a t-test showed that there was a significant difference in NO$_2$ levels before and after lockdown, with p<0.05. Fig 1(g-i) shows NO$_2$ levels before and after lockdown and improvement in NO$_2$ levels during lockdown. The average NO$_2$ level in the country more than halved during the lockdown period. Vehicles are the major contributor of NO$_2$ in ambient air (Ramachandran et al. 2013; US EPA 2019), and a large reduction in NO$_2$ levels is expected. On March 24th, 2020, soon after the implementation of lockdown, an approximately 60% reduction in traffic was observed. In Delhi, the morning traffic congestion in 2019 was between 50 and 80 %, but it was reduced to single digit values ranging from 0 to 6 %. Similarly, in Bombay, the traffic congestion in 2019 during morning rush hours was 60 to 80%, and it decreased to <5%. A similar trend was observed throughout the lockdown period (Tom Tom Traffic Index, 2020). Among the states, the lowest level of NO$_2$ before lockdown was observed in the states of Jammu and Kashmir, Punjab, Kerala, Tamil Nadu and Andhra Pradesh. Similar to other pollutants, such as PM$_{10}$ and PM$_{2.5}$, the highest decrease percentage in NO$_2$ levels as a result of lockdown was observed in West Bengal. In Howrah and Kolkata (West Bengal), all the monitoring stations in the traffic zone recorded 66 to 85% reduction of NO$_2$. Similar reductions
were noticed in the high traffic zones of Noida, Greater Noida and Ghaziabad (52-74%), Haryana (74%), Kanpur (54-66%), Chennai (67%), Udaipur (68%), Kota (57%), Jodhpur (55%), Jaipur (66%), Mizoram (74%), Mumbai (67-88%), Nagpur (60%), Navi Mumbai (85%), Tirupati (76%), and Thiruvananthapuram (65%). Reductions were also observed in traffic zones of Delhi (50 to 75%), Madhya Pradesh (60 to 70%), and Bangalore (58-80%). Among petrol and diesel vehicles, a higher contribution of NO\textsubscript{2} is from diesel vehicles (European Union 2019). The fact that a major portion of the vehicles registered in the country are diesel vehicles (Government of India 2015) could also have contributed to the higher reduction of NO\textsubscript{2}. In Delhi, compressed natural gas (CNG) vehicles constitute a significant portion of the vehicles on the road. Studies have confirmed that although CNG vehicles emit fewer pollutants than petrol and diesel vehicles with respect to PM\textsubscript{10}, PM\textsubscript{2.5} and SO\textsubscript{2}, there is not much reduction in NO\textsubscript{2} emissions (Narain and Krupnick 2011).

The overall country averages using the interpolated value for SO\textsubscript{2} were 14 µg/m\textsuperscript{3} and 11 µg/m\textsuperscript{3} before and after lockdown, respectively. Statistical analysis using a t-test showed that there was a significant difference in SO\textsubscript{2} levels before and after lockdown with p<0.05. Fig 1(j-l) shows SO\textsubscript{2} levels before and after lockdown and improvement in SO\textsubscript{2} levels during lockdown. During the lockdown period, the lowest SO\textsubscript{2} levels were observed in the southern states, Kerala and Tamil Nadu. India is the world's largest emitter of SO\textsubscript{2}, and its emissions are mainly from 45 hotspots in the country (Shagun Kapil 2019). Out of the 45 hotspots, 43 have coal-based electricity generation. In Talcher Coalfields, Orissa, an approximately 50% reduction of SO\textsubscript{2} was observed, although the coal mines were still operational, albeit at reduced capacity. A significant reduction in SO\textsubscript{2} was also observed in many industrial belts across the country. For example, in Jahangirpuri- Delhi (70%), Pusa- Delhi (50%), GIDC, Ankleshwar- Gujarat (78%), Phase-4 GIDC, Vatva- Gujarat (83%), Industrial belt near to Chhatrapati Shivaji International Airport- Mumbai (83%), Mahape, Navi Mumbai (59%), and RIICO Industrial Area III- Bhiwadi (72%).

The overall country averages using the interpolated values for O\textsubscript{3} were 35 µg/m\textsuperscript{3} and 37 µg/m\textsuperscript{3} before and after lockdown, respectively. The slight increase can be attributed to the increased photochemical activity due to the decrease in particulate matter concentration (Dang and Liao 2017; Li et al. 2018). Statistical analysis using t-test showed that there is no significant difference in O\textsubscript{3} level before and after lockdown with p>0.05. Fig 1 (m-o) shows O\textsubscript{3} levels before and after lockdown and improvement in O\textsubscript{3} levels during lockdown. The highest average O\textsubscript{3} concentration before lockdown was observed in some areas of Rajasthan and Madhya Pradesh. During the
lockdown period, a decrease in O₃ concentration was observed in the southern, some parts of the western, and some northeastern states. At the same time, Madhya Pradesh, some areas of Rajasthan, a few Northern states, and West Bengal showed slight increases in O₃ concentration levels. The highest increase was observed in the eastern regions and in the northern states of Delhi, Uttaranchal, Haryana, and Uttar Pradesh, where the PM₁₀ concentrations were higher before the lockdown period.

The country experienced an overall increase in AQI levels, as shown in Fig 1(p). The highest improvement in AQI was seen in West Bengal (61.89%), followed by Arunachal Pradesh (47.80%) and Meghalaya (47.58%). The least change was observed in Orissa (3.55%). The AQI values in Orissa before and after lockdown were 132.49 and 127.78, respectively. Even before lockdown, the AQI in the southern states was in the satisfactory range. Among the major cities, the highest percentage reduction in AQI was in Jaipur, followed by Kolkata, Mumbai, Pune and New Delhi. The lowest reduction was observed in Chennai. The other major cities, such as Bangalore, Hyderabad and Ahmedabad, had intermediate percentage reductions in AQI values. Although the lowest AQI value before lockdown was observed in Chennai, the lowest value after lockdown was found in Jaipur. Additionally, the highest value before and after lockdown was observed in New Delhi.

The interpolated values of pollutant concentrations were compared with NAAQS to determine the number of days when it exceeded the permissible limits (Fig 2(a & b)). It was observed that gaseous pollutants (NO₂, SO₂ and O₃) were within the permissible limits before and after lockdown. In the case of West Bengal, Telangana, Meghalaya, Maharashtra, Kerala, Karnataka, Chandigarh and Andhra Pradesh, there was no day when the state average value exceeded the permissible limits as prescribed by CPCB in the case of PM₁₀ after the implementation of lockdown. The percentage reduction of pollution in all three categories of areas (traffic, residential, and industrial) was approximately 40% after the implementation of COVID-19 lockdown, as shown in Fig. 3. As per the 2011 census data, the most populated cities in India are Mumbai, Delhi, Bangalore, Hyderabad, Ahmedabad, Chennai, Kolkata, Surat, Pune and Jaipur. Except for Surat, data were available for all these cities. For PM₂.₅, most of the cities showed a more than 50% reduction in concentration after the start of lockdown, as shown in Fig. 4. In all the cities, the mean concentration values came below the CPCB standards for ambient air, and the daily average values stayed within limits for approximately 95% of days. Similar observations were also observed in the case of PM₁₀. Its mean concentration fell to within the CPCB limits in all cities except Delhi,
where it just crossed the limit. The concentration decreased by approximately 47% in these cities, and the values remained within the limit for approximately 91% of the days.

In the case of NO\textsubscript{2} and SO\textsubscript{2}, the ambient air concentrations were within the limits in all these cities even before lockdown. The lockdown further reduced their concentrations by 30.45 µg/m\textsuperscript{3} to 14.64 µg/m\textsuperscript{3} for NO\textsubscript{2} and 14 µg/m\textsuperscript{3} to 11 µg/m\textsuperscript{3} for SO\textsubscript{2}. Their values exceeded the permissible limits (80 µg/m\textsuperscript{3}) for a very few days (<1% days). Ozone, on the other hand, showed a reverse trend due to lockdown. In New Delhi, Kolkata, Chennai and Hyderabad, the concentration of ozone increased, ranging from 3.8 to 38.3%.

Correlation analysis can be used to explore the associations between a pair of pollutants. Highly correlated concentrations are indicative of common sources for both pollutants (Binaku and Schmeling 2017; Ebqa’ai and Ibrahim 2017; Zhu et al. 2017; Núñez-Alonso et al. 2019). The values of the Pearson coefficient of the pollutant pairs before and after the lockdown period are given in Table 2. The Pearson correlation is significant for a pair when p<0.05. The PM\textsubscript{10}-PM\textsubscript{2.5} pair is positively correlated before (0.880) and after (0.746) the lockdown, which suggests a common source for most of these pollutants. The coefficients for the pairs PM\textsubscript{10}-NO\textsubscript{2} and PM\textsubscript{2.5}-NO\textsubscript{2} are also significant. Motor vehicles are a common source of particulates, and NO\textsubscript{2} explains this correlation. The higher correlation between reductions in PM\textsubscript{2.5} and NO\textsubscript{2}, compared to the correlations of their concentrations in ambient air before and after lockdown, perhaps indicates that their reductions to a great extent can be attributed to the removal of diesel vehicles from roads due to lockdown. An interesting observation was the positive correlation of PM\textsubscript{10} and PM\textsubscript{2.5} with O\textsubscript{3} after the lockdown period. This probably indicates that a significant source of PM after lockdown is photochemical reactions (Mangia et al. 2015) that also result in the formation of O\textsubscript{3} (North Earth Observatory 2003). With most of the anthropogenic sources of primary particulate matter cut down, a good proportion of the available particulate matter might be the secondary particulate matter formed due to chemical reactions between various existing pollutants. Before the lockdown period, PM\textsubscript{10}/O\textsubscript{3} and PM\textsubscript{2.5}/O\textsubscript{3} were either uncorrelated or negatively correlated. There is no significant correlation in the case of NO\textsubscript{2}/SO\textsubscript{2}, SO\textsubscript{2}/O\textsubscript{3} and NO\textsubscript{2}/O\textsubscript{3} both before and after the lockdown period, indicating that these pollutant pairs are from different sources.

Table 2 Correlation among the selected pollutants before lockdown (N=158)
Perceived air quality

On conducting $\chi^2$ tests on the responses obtained from rural and urban populations, a significant difference in opinion was noticed between them; $\chi^2 (2, N=1750) = 43.99, p < 0.05$. Urban responders felt higher improvement in air quality during the lockdown (64% to 49%). The observed effect size was Cramer’s V = 0.2, indicating a small effect size in the difference in perception. This shows that although there is a significant difference in the opinion, the people in both rural and urban environments have perceived improvement in air quality. Considering the different types of locality (residential, traffic, industrial), a significant difference in opinion was observed, $\chi^2 (2, N=1395) = 18.987, p <0.05$. The observed effect size in this scenario was much smaller (Cramer’s V = 0.1).

The order of improvement of air quality perception among different localities was Industries > Near to traffic junctions > Residential > Near to hospital, as shown in fig 5. Nearness to hospital was considered a separate category expecting more traffic near hospitals due to the pandemic situation. More than half of the respondents in all major cities perceived improvement in air quality: Delhi (100%), Ahmedabad (85%), Chennai (83%), Mumbai (80%), Bangalore (65%), Jaipur (66%) and Hyderabad (54%).

A nonparametric (independent sample Kruskalwallis) test was conducted to establish differences in opinion among different zones in India. In the case of visibility, the opinion on improvement was found to be similar on pairwise comparison across all the zones in the country, except in the case of Southern zonal council vs. Northern zonal council and Southern zonal council vs. Central zonal council, with p value of < 0.05. Similarly, in the case of perception on improvement of health, significant differences in responses were obtained from the North Eastern vs. Central and Western zonal council and Northern vs. Central zonal council, with a p value of <0.05. In the case of indoor air quality (IAQ), a significant difference in opinion was obtained from the northern
and southern zonal council, as in the case of visibility. The mean rating (on a five-point scale) of air quality perception in the case of rural areas increased from 3.5 to 4.3, whereas in the case of urban areas, it increased from 2.9 to 4.12. The improvement in the perception of air quality is shown in Fig. 6 (a). In a zone-wise comparison, people from all zones felt air quality to be ‘excellent’ after lockdown, as shown in Fig. 6 (b). Responses from major cities in India were analyzed separately, and it was found that the mean perception of Ahmedabad changed from 2.4 to 4.1, Bangalore and Hyderabad changed from 2.92 to 4, Chennai changed from 2.7 to 4.2, Delhi changed from 2.2 to 4.5, Jaipur changed from 2.8 to 4.3, Kolkata and Mumbai changed from 2.6 to 4.2, and Pune and Surat changed from 3 to 4, as represented in fig 6 (c). This indicates that respondents from major cities across India perceived improvement in air quality during this lockdown period. The obtained perception scales and geolocations were directly subjected to geo-spatial analysis using ArcGIS. The maps in Fig. 7 (a-c) indicate the perception before and after lockdown and the change in perception due to the lockdown.

Most people perceived the air as moderately polluted before lockdown. From the plots obtained for perception of air quality after lockdown, it is clear that most people perceived air quality as satisfactory or good. Therefore, it can be interpreted that the lockdown has created a positive feeling among people regarding the air quality in the country.

The major sources of pollution as perceived by the respondents before lockdown were Vehicular Pollution > Road dust > Construction works > Industries > Road side burning > Burning of agricultural waste > Power plant. However, after lockdown, the order was Household emissions > Solid waste burnings > Traffic > None > Industrial activities > others. Other factors included burning of crackers, spraying of disinfectant chemicals and smoking. The perception of sources among different localities and zonal councils is given as supplementary material.

The results from Google Trend Analysis (https://trends.google.com/trends/?geo=US) showed that terms related to air pollution (‘air quality’, ‘air quality index’, ‘air pollution’, ‘AQI’) were trending from October to December 2019, as shown in Fig. 8. As per the Google Trend Analysis, maximum searches occurred in North Indian states such as Delhi, Haryana, Uttar Pradesh, Punjab, Uttarakhand, and Himachal Pradesh. October to December is the time period every year North and North West India face severe air pollution due to stubble burning compounded by meteorological conditions (Rizwan et al. 2013; Patel 2019). The trend that declined drastically after the annual pollution episode continued decreasing to the lockdown period, albeit at a smaller rate, except for a small spike on 22/03/2020, the day when the Janata curfew was implemented. This trend can be interpreted as a lack
of influence of media on the perception of air quality by the public. Similar inferences were made by Searle et al., (2020) and Szmuda et al.,(2020).

**Relationship between PAQ and AAQ**

Our perception survey showed that approximately 60% of the respondents perceived improvement in air quality during the COVID-19 lockdown compared to the pre-lockdown period. The analysis of the air quality monitoring data showed that from the pre-lockdown to lockdown period, the AQI improved by 40% in the country. To have a quantitative comparison, the perceived air quality was obtained on a rating scale from 1 to 5 (Poor to Good). The pollutant concentrations were converted to the same rating scale (1 to 5) as per the break points proposed by CPCB. The results from the paired t-test showed that there was a significant difference (p<0.05) in air quality perception before and after lockdown (*Table 3*). Similarly, there is a significant difference (p<0.05) in actual air quality before and after lockdown. However, there is no significant difference (p>0.05) between the pairs ‘air quality perception before lockdown - actual air quality before lockdown’ and ‘air quality perception after lockdown - actual air quality after lockdown’. This shows that there is a clear association between air quality perception and actual air quality. On conducting the test of significance between air quality perception and the converted rating scale of actual air quality, interesting results were found. There was no significant difference (p>0.05) between air quality perception and PM$_{10}$ level, but there was a significant difference between the perception and levels of SO$_2$, NO$_2$ and O$_3$ (P=0.00). This shows that among various pollutants, PM influenced perception most, possibly because of its contribution to visibility. Several studies have shown a clear association between PM$_{10}$ levels and visibility, with an increase in PM$_{10}$ levels resulting in lower visibility (Zhao et al. 2013; Huang et al. 2016). In earlier days, before the invention of air quality monitoring instruments, visibility was the parameter that was used to assess the air quality. Visibility impairment is caused by scattering and absorption of visible light by the suspended particulates and gaseous pollutants present in the atmosphere (Hyslop 2009; Lee et al. 2015; Majewski et al. 2015). In urban environments, visibility impairment is closely associated with pollutants emitted from anthropogenic sources such as automobile exhaust, combustion of fuel, emission from industries, etc. (Tsai et al. 2007; Deng et al. 2008; Majewski et al. 2015). It was also observed that this visibility impairment is mainly due to airborne particulate matter (Malm and Day 2001; Tsai et al. 2003).

*Table 3* Results of paired sample t-test
| Paired Differences | Mean | Std. Deviation | Std. Error Mean | Mean | 95% Confidence Interval of the Difference | t    | Sig. (2-tailed) |
|--------------------|------|----------------|----------------|------|------------------------------------------|------|----------------|
|                    |      |                |                |      | Lower | Upper |            |      |               |
| AQ BL– AQ AL       | -0.80952 | 1.32737 | 0.28966 | -1.41373 | -0.20531 | -2.795 | 0.011 |
| AP BL– AP AL       | -0.95238 | 0.58959 | 0.12866 | -1.22076 | -0.68400 | -7.402 | 0.000 |
| APBL– AQ BL        | 0.00000 | 0.94868 | 0.20702 | -0.43184 | 0.43184 | 0.000 | 1.000* |
| AP AL– AQ AL       | 0.14286 | 0.91026 | 0.19863 | -0.27149 | 0.55720 | 0.719 | 0.480* |
| AP BL - PM\textsubscript{10} BL | -0.09524 | 0.62488 | 0.13636 | -0.37968 | 0.18920 | -0.698 | 0.493* |
| AP AL - PM\textsubscript{10} AL | 0.14286 | 0.65465 | 0.14286 | -0.15514 | 0.44085 | 1.000 | 0.329* |
| AP BL – PM\textsubscript{2.5} BL | -0.33333 | 0.73030 | 0.15936 | -0.66576 | -0.00091 | -2.092 | 0.049 |
| AP AL – PM\textsubscript{2.5} AL | -0.33333 | 0.65828 | 0.14365 | -0.63298 | -0.03369 | -2.320 | 0.031 |
| AP BL - NO\textsubscript{2} BL | -1.71429 | 0.46291 | 0.10102 | -1.92500 | -1.50357 | -16.971 | 0.000 |
| AP AL - NO\textsubscript{2} AL | -0.85714 | 0.35857 | 0.07825 | -1.02036 | -0.69392 | -10.954 | 0.000 |
| APBL - SO\textsubscript{2} BL | -1.80952 | 0.40237 | 0.08781 | -1.99268 | -1.62637 | -20.608 | 0.000 |
| AP AL - SO\textsubscript{2} AL | -0.85714 | 0.35857 | 0.07825 | -1.02036 | -0.69392 | -10.954 | 0.000 |
| AP BL - O\textsubscript{3} BL | -1.80952 | 0.40237 | 0.08781 | -1.99268 | -1.62637 | -20.608 | 0.000 |
The odds ratio (OR), often used in medical statistics, represents the odds that an outcome will occur given a particular exposure compared to the odds of the outcome occurring in the absence of that exposure (Szumilas 2010). It is extensively used to analyze the relationship between exposure to pollutants and its health impacts (Baxter et al. 2010; Lee et al. 2014; Yorifuji et al. 2014; Klompmaker et al. 2019). It is also used in air quality perception studies (Malenka et al. 1993; VanderWeele and Vansteelandt 2010; Voda et al. 2020). To quantify how the change in air quality actually changed the perception, responses from a city with one of the highest reductions of pollution (Delhi -72 responses) and an area where there was only a small reduction in pollution after lockdown (Rural Telangana -39 responses) were used to calculate the odds ratio. The details of the responses are given in Table 4.

**Table 4** Inputs for the determination of odds ratio

|                      | Delhi       | Rural Telangana |
|----------------------|-------------|-----------------|
| No of respondents perceived significant improvement in air quality | 57 \(N_{pi}\) | 7 \(N_{pi}\) |
| No of respondents perceived no improvement in air quality       | 15 \(N_{ni}\) | 32 \(N_{ni}\) |
The OR obtained is 17, which indicates that the perception improvement in air quality is highly dependent on the actual improvement in the air quality. Higher odds ratios indicate higher dependence between PAQ and AAQ.

**Qualitative interpretation of the suggestions**

The words were decoded from the suggestions based on the frequency of appearance. The suggestions given by the respondents were to lift the lockdown scientifically, to implement strict regulations with respect to traffic, industries, vehicular emissions and trash burning on road margins, living in harmony with nature, strengthening public transportation and adoption of carpooling systems, promotion of E-vehicles and bio-fuels, plantation of trees, installation of air quality monitors across the country and creating awareness among the public about the improvement in air quality levels and maintenance of the same.

**Conclusion**

From this study, it is evident that there is significant improvement in the actual and perceived air quality in India after the COVID-19-induced lockdown. Approximately 60% of the respondents perceived improvement in air quality, and there was approximately 40% improvement in the monitored air quality across the country. It is evident that the respondents perceived improvement in air quality without the influence of media. The reduction in air pollution was investigated with respect to three different zones. Major traffic zones across the country have experienced significant improvement in the NO$_2$ level due to the decrease in vehicular load. Similarly, a significant reduction in SO$_2$ levels was observed in industrial belts and coal mines. The correlation matrix developed gave a clear association between the pollutants and the possible sources. During the lockdown period, an increased photochemical reaction was observed, which led to an increase in the levels of ozone at many locations. Along with improvements in air quality, significant improvements in visibility, indoor air quality and health were perceived by the respondents. The perception of improvement in air quality was influenced mainly by the reduction in particulate matter. The odds ratio showed a very strong dependence of perception on actual air quality. Suggestions by the public for maintaining air quality even after lifting the COVID-19 lockdown are also given in this study.

**Declarations**

**Funding:** No funds received

**Conflicts of interest/Competing interests:** The authors declare that they have no known competing interests.

**Availability of data and material:** Added as supplementary material

**Code availability:** Not applicable
The study involved analysis of perception of the general public on improvement in air quality during COVID-19 lockdown. No approval is required from any committee to conduct such studies in India. No personal information was collected from any responders during our perception study that would reveal the identity of the respondent. Further, no individual responses are presented in the manuscript, but only results of aggregate analysis.

References

Bao R, Zhang A (2020) Journal P. Sci Total Environ 139052. doi: 10.1016/j.scitotenv.2020.139052

Baxter LK, Wright RJ, Paciorek CJ, et al (2010) Effects of exposure measurement error in the analysis of health effects from traffic-related air pollution. J Expo Sci Environ Epidemiol 20:101–111. doi: 10.1038/jes.2009.5

Binaku K, Schmeling M (2017) Multivariate statistical analyses of air pollutants and meteorology in Chicago during summers 2010-2012. Air Qual Atmos Heal 10:1227–1236. doi: 10.1007/s11869-017-0507-7

Brandt EB, Biagini JM, Ryan PH (2015) Air pollution and allergic diseases. 27:724–735. doi: 10.1097/MOP.0000000000000286

Brody SD, Peck BM, Highfield WE (2004) Examining localized patterns of air quality perception in Texas: A spatial and statistical analysis. Risk Anal 24:1561–1574. doi: 10.1111/j.0272-4332.2004.00550.x

Brosschot JF, Gerin W, Thayer JF (2006) The perseverative cognition hypothesis: A review of worry, prolonged stress-related physiological activation, and health. J Psychosom Res 60:113–124. doi: 10.1016/j.jpsychores.2005.06.074

Chen H, Guo J, Wang C, et al Clinical characteristics and intrauterine vertical transmission potential of COVID-19 infection in nine pregnant women: a retrospective review of medical records. Lancet 395:809–815. doi: 10.1016/S0140-6736(20)30360-3

Costa LG, Cole TB, Dao K, et al (2020) Pharmacology & Therapeutics Effects of air pollution on the nervous system and its possible role in neurodevelopmental and neurodegenerative disorders. Pharmacol Ther 107523. doi: 10.1016/j.pharmthera.2020.107523
CPCB (2020a) Central Control Room for Air Quality Management - All India. https://app.cpcbccc.com/CCR/#/caaqm-dashboard-all/caaqm-landing. Accessed 8 Apr 2020

CPCB (2020b) National Network. https://app.cpcbccc.com/CCR_docs/National_Network.pdf

CPCB (2014) National Air Quality Index

Cristina M, Abbà A, Bertanza G, et al (2020) Science of the Total Environment Lockdown for CoViD-2019 in Milan: What are the effects on air quality? Sci Total Environ 732:139280. doi: 10.1016/j.scitotenv.2020.139280

Dang R, Liao H (2017) Radiative forcing and health impact of aerosols and ozone in China as the consequence of clean air actions over 2012-2017. 0–2. doi: 10.1029/2019GL084605

Dantas G, Siciliano B, Boscaro B, et al (2020) The impact of COVID-19 partial lockdown on the air quality of the city of Rio de Janeiro, Brazil. Sci Total Environ 729:139085. doi: 10.1016/j.scitotenv.2020.139085

Davis ME (2012) Recessions and health: The impact of economic trends on air pollution in California. Am J Public Health 102:1951–1956. doi: 10.2105/AJPH.2012.300658

Davies ME, Laden F, Hart JE, et al (2010) Economic activity and trends in ambient air pollution. Environ Health Perspect 118:614–619. doi: 10.1289/ehp.0901145

Deng X, Tie X, Wu D, et al (2008) Long-term trend of visibility and its characterizations in the Pearl River Delta (PRD) region, China. Atmos Environ 42:1424–1435. doi: 10.1016/j.atmosenv.2007.11.025

Ebqa’i M, Ibrahim B (2017) Application of multivariate statistical analysis in the pollution and health risk of traffic-related heavy metals. Environ Geochem Health 39:1441–1456. doi: 10.1007/s10653-017-9930-9

Elliott SJ, Cole DC, Krueger P, et al (1999) The Power of Perception: Health Risk Attributed to Air Pollution in an Urban Industrial Neighbourhood. 19:

Engen T (1991) Odor sensation and memory. New York: Praeger

Environmental Systems Research Institute (2016) How Kriging works. In: ESRI. https://desktop.arcgis.com/en/arcmap/10.3/tools/3d-analyst-toolbox/how-kriging-works.htm#:~:text=The%20kriging%20formula,Kriging%20is%20similar&text=Thus%2C%20in%20ordinary%20kriging%20the%20values%20around%20the%20prediction%20location. Accessed 8 Apr 2020

Escudero M, Segers A, Kranenburg R, et al (2019) Analysis of summer O 3 in the Madrid air basin with the LOTOS-EUROS chemical transport model. 14211–14232

European Union (2019) Air quality: traffic measures could effectively reduce NO2 concentrations by 40% in Europe’s cities. https://ec.europa.eu/jrc/en/news/air-quality-traffic-measures-could-effectively-reduce-no2-concentrations-40-europe-s-cities. Accessed 8 Oct 2020
Evans GW, Colome SD, Shearer DF (1988) Psychological Reactions to Air Pollution. 15:

Gorai AK, Tchounwou PB, Mitra G (2017) HHS Public Access. 17:951–964. doi: 10.4209/aaqr.2016.08.0374.Spatial

Government of India (2019) Zonal Council. In: Minist. Home Aff. https://www.mha.gov.in/zonal-council. Accessed 8 May 2020

Government of India (2015) Total Number of Registered Motor Vehicles in India. https://data.gov.in/catalog/total-number-registered-motor-vehicles-india?filters%5Bfield_catalog_reference%5D=92126&format=json&offset=0&limit=6&sort%5Bcreated%5D=desc. Accessed 8 Oct 2020

Guo Y, Liu F, Lu Y, et al (2016) Factors Affecting Parent ’ s Perception on Air Quality — From the Individual to the Community Level. Int J Environ Res Public Health 13:1–14. doi: 10.3390/ijerph13050493

Gurjar BR, Ravindra K, Nagpure AS (2016) Air pollution trends over Indian megacities and their local-to-global implications. Atmos Environ. doi: 10.1016/j.atmosenv.2016.06.030

Guttikunda SK, Nishadh KA, Jawahar P (2019) Air pollution knowledge assessments (APnA) for 20 Indian cities. Urban Clim 27:124–141. doi: 10.1016/j.uclim.2018.11.005

Howel D, Moffatt S, Bush J, et al (2003) Public views on the links between air pollution and health in Northeast England. 91:163–171. doi: 10.1016/S0013-9351(02)00037-3

Huang C, Wang Y, Li X, et al (2020) Articles Clinical features of patients infected with 2019 novel coronavirus in Wuhan , China. 6736:1–10. doi: 10.1016/S0140-6736(20)30183-5

Huang L, Chen M, Hu J (2016) Twelve-Year Trends of PM10 and Visibility in the Hefei Metropolitan Area of China. Adv Meteorol 2016:25–27. doi: 10.1155/2016/4810796

Hyslop NP (2009) Impaired visibility: the air pollution people see. Atmos Environ 43:182–195. doi: 10.1016/j.atmosenv.2008.09.067

ICRA (2020a) Covid-19 Impact: Short-term negative impact on the Healthcare sector

ICRA (2020b) Ripple effect of COVID outbreak to impact India Inc

ICRA (2020c) Indian Port Sector: Global impact of the corona virus a negative for exim volumes at Indian ports - Trends & Outlook

Kerimray A, Baimatova N, Ibragimova OP, et al (2020) Science of the Total Environment Assessing air quality changes in large cities during COVID-19 lockdowns: The impacts of traffic-free urban conditions in Almaty, Kazakhstan. Sci Total Environ 730:139179. doi: 10.1016/j.scitotenv.2020.139179
Klompmaker JO, Janssen NAH, Bloemsma LD, et al (2019) Associations of combined exposures to surrounding green, air pollution, and road traffic noise with cardiometabolic diseases. Environ Health Perspect 127:1–15. doi: 10.1289/EHP3857

Kohlhuber M, Mielck A, Weiland SK, Bolte G (2006) Social inequality in perceived environmental exposures in relation to housing conditions in Germany. Environ Res 101:246–255. doi: 10.1016/j.envres.2005.09.008

Kumar Jha D, Sabesan M, Das A, et al (2011) Evaluation of Interpolation Technique for Air Quality Parameters in Port Blair, India. Univers J Environ Res Technol 1:301–310

Lan G, Yuan Z, Maddock JE, et al (2016) Public perception of air pollution and health effects in Nanchang, China. doi: 10.1007/s11869-016-0397-0

Landrigan PJ, Fuller R, Acosta NJR, et al (2017) The Lancet Commissions The Lancet Commission on pollution and health. 6736:. doi: 10.1016/S0140-6736(17)32345-0

Lee JY, Jo WK, Chun HH (2015) Long-term trends in visibility and its relationship with mortality, air-quality index, and meteorological factors in selected areas of Korea. Aerosol Air Qual Res 15:673–681. doi: 10.4209/aaqr.2014.02.0036

Lee JY, Lee SB, Bae GN (2014) A review of the association between air pollutant exposure and allergic diseases in children. Atmos Pollut Res 5:616–629. doi: 10.5094/APR.2014.071

Lelieveld J, Evans JS, Fnais M, et al (2015) The contribution of outdoor air pollution sources to premature mortality on a global scale. doi: 10.1038/nature15371

Li K, Jacob DJ, Liao H, et al (2018) Anthropogenic drivers of 2013 – 2017 trends in summer surface ozone in China. 1–6. doi: 10.1073/pnas.1812168116

Li Z, Folmer H, Xue J (2016) Perception of Air Pollution in the Jinchuan Mining Area, China: A Structural Equation Modeling Approach. Int J Environ Res 13:1–18. doi: 10.3390/ijerph13070735

Liu H, Kobernus M, Liu H (2017) Public Perception Survey Study on Air Quality Issues in Wuhan, China. 1194–1218. doi: 10.4236/jep.2017.810075

Lloyd C, Smith J, Weinger K (2005) Stress and diabetes: A review of the links. Diabetes Spectr 18:121–127. doi: 10.2337/diaspect.18.2.121

Mahato S, Pal S, Ghosh KG (2020) Effect of lockdown amid COVID-19 pandemic on air quality of the megacity Delhi, India. Sci Total Environ 730:139086. doi: 10.1016/j.scitotenv.2020.139086

Majewski G, Rogula-Kozlowska W, Czechowski PO, et al (2015) The impact of selected parameters on visibility: First results from a long-term campaign in Warsaw, Poland. Atmosphere (Basel) 6:1154–1174.
doi: 10.3390/atmos6081154

Malenka DJ, Baron JA, Johansen S, et al (1993) The framing effect of relative and absolute risk. J Gen Intern Med 8:543–548. doi: 10.1007/BF02599636

Mally KV (2016) Perceptions of air quality in Ljubljana. Dela 2016:77–88. doi: 10.4312/dela.46.3.67-88

Malm WC, Day DE (2001) Estimates of aerosol species scattering characteristics as a function of relative humidity. Atmos Environ 35:2845–2860. doi: 10.1016/S1352-2310(01)00077-2

Mangia C, Cervino M, Gianicolo EAL (2015) Secondary particulate matter originating from an industrial source and its impact on population health. Int J Environ Res Public Health 12:7667–7681. doi: 10.3390/ijerph120707667

Ministry of Home Affairs (2020) Government of India issues Orders prescribing lockdown for containment of COVID-19 Epidemic in the country. In: Press Inf. Bur. Gov. India. https://pib.gov.in/newsite/PrintRelease.aspx?relid=200655

Monks PS, Archibald AT, Colette A, et al (2015) Tropospheric ozone and its precursors from the urban to the global scale from air quality to short-lived climate forcer. 8889–8973. doi: 10.5194/acp-15-8889-2015

MORTH (2019) Road Transport Year Book (2016-17)

Muhammad S, Long X, Salman M (2020) Science of the Total Environment COVID-19 pandemic and environmental pollution: A blessing in disguise? Sci Total Environ 728:138820. doi: 10.1016/j.scitotenv.2020.138820

Murukutla N, Kumar N, Mullin S (2019) A review of media effects: implications for media coverage of air pollution and cancer. Ann Cancer Epidemiol 3:3–3. doi: 10.21037/ace.2019.07.03

Nagpure AS, Gurjar BR, Martel J (2014) Atmospheric pollution. 5:371–380. doi: 10.5094/APR.2014.043

Narain U, Krupnick A (2011) The Impact of Delhi’s CNG Program on Air Quality. SSRN Electron J. doi: 10.2139/ssrn.969727

NASA Earth Observatory (2020) Airborne Nitrogen Dioxide Plummets Over China. https://earthobservatory.nasa.gov/images/146362/airborne-nitrogen-dioxide-plummets-over-china

Nikolopoulou M, Kleissl J, Linden PF (2009) Perception Of Air Pollution And Comfort In The Urban Environment

Norbäck D, Lu C, Zhang Y, et al (2019) Sources of indoor particulate matter (PM) and outdoor air pollution in China in relation to asthma, wheeze, rhinitis and eczema among pre-school children:
Synergistic effects between antibiotics use and PM 10 and second hand smoke. Environ Int 125:252–260. doi: 10.1016/j.envint.2019.01.036

North Earth Observatory (2003) Chemistry in the Sunlight. https://earthobservatory.nasa.gov/features/ChemistrySunlight/chemistry_sunlight3.php

Núñez-Alonso D, Pérez-Arribas LV, Manzoor S, Cáceres JO (2019) Statistical Tools for Air Pollution Assessment: Multivariate and Spatial Analysis Studies in the Madrid Region. J Anal Methods Chem 2019:. doi: 10.1155/2019/9753927

Oltra C, Sala R (2016) Perception of risk from air pollution and reported behaviors: a cross-sectional survey study in four cities. J Risk Res 9877:1–16. doi: 10.1080/13669877.2016.1264446

Pantavou K, Psiloglou B, Lykoudis S, et al (2018) Perceived air quality and particulate matter pollution based on field survey data during a winter period. Int J Biometeorol 62:2139–2150. doi: 10.1007/s00484-018-1614-3

Patel P (2019) Tackling Delhi’s Air Pollution Problem. ACS Cent Sci 5:3–6. doi: 10.1021/acscentsci.9b00009

R.B. Singh (2016) Progress in Indian Geography

Ramachandran A, Jain NK, Sharma SA, Pallipad J (2013) Recent trends in tropospheric NO2 over India observed by SCIAMACHY: Identification of hot spots. Atmos Pollut Res 4:354–361. doi: 10.5094/APR.2013.040

Rizwan SA, Nongkynrih B, Gupta SK (2013) Air pollution in Delhi: Its Magnitude and Effects on Health. Indian J Community Med 38:4–8. doi: 10.4103/0970-0218.106617

Schierhorn F, Kastner T, Kuemmerle T, et al (2019) Large greenhouse gas savings due to changes in the post-Soviet food systems. Environ Res Lett 14:. doi: 10.1088/1748-9326/ab1cf1

Searle TN, Al-Niaimi F, Ali FR (2020) Dermatological insights from Google Trends: what does the public think is important during COVID-19 lockdown? Clin Exp Dermatol 0–2. doi: 10.1111/ced.14319

Semenza JC, Wilson DJ, Parra J, et al (2008) Public perception and behavior change in relationship to hot weather and air pollution $. 107:401–411. doi: 10.1016/j.envres.2008.03.005

Shagun Kapil (2019) Maharashtra, Gujarat top sulphur dioxide polluters in India. In: Down To Earth. https://www.downtoearth.org.in/news/air/maharashtra-gujarat-top-sulphur-dioxide-polluters-in-india-66250. Accessed 8 Dec 2020
Sharma S, Zhang M, Gao J, et al (2020) Science of the Total Environment Effect of restricted emissions during COVID-19 on air quality in India. Sci Total Environ 728:138878. doi: 10.1016/j.scitotenv.2020.138878

Silver W (1991) Physiological factors in nasal trigeminal chemoreception. In: Green BG, Mason JR, Kare MR, editors. Chemical senses, vol2, Irritation. Marcel Dekker, New York

Sucker K, Both R, Bischoff M, et al (2008) Odor frequency and odor annoyance. Part I: Assessment of frequency, intensity and hedonic tone of environmental odors in the field. Int Arch Occup Environ Health 81:671–682. doi: 10.1007/s00420-007-0259-z

Sullivan GM, Feinn R (2012) Using Effect Size—or Why the P Value Is Not Enough. J Grad Med Educ 4:279–282. doi: 10.4300/jgme-d-12-00156.1

Sunyer J, Forsberg B, Go T, et al (2007) Annoyance due to air pollution in Europe. doi: 10.1093/ije/dym042

Szmuda T, Ali S, Hetzger TV, et al (2020) Are online searches for the novel coronavirus (COVID-19) related to media or epidemiology? A cross-sectional study. Int J Infect Dis 97:386–390. doi: 10.1016/j.ijid.2020.06.028

Szumilas M (2010) Explaining Odds Ratios. J Can Acad Child Adolesc Psychiatry 19:227–229. doi: 10.1136/bmj.c4414

Tsai YI, Kuo SC, Lee WJ, et al (2007) Long-term visibility trends in one highly urbanized, one highly industrialized, and two Rural areas of Taiwan. Sci Total Environ 382:324–341. doi: 10.1016/j.scitotenv.2007.04.048

Tsai YI, Lin YH, Lee SZ (2003) Visibility variation with air qualities in the metropolitan area in southern Taiwan. Water Air Soil Pollut 144:19–40. doi: 10.1023/A:1022901808656

US EPA (2019) Nitrogen Dioxide (NO2) Pollution. https://www.epa.gov/no2-pollution/basic-information-about-no2#What is NO2. Accessed 8 Jun 2020

VanderWeele TJ, Vansteelandt S (2010) Odds ratios for mediation analysis for a dichotomous outcome. Am J Epidemiol 172:1339–1348. doi: 10.1093/aje/kwq332

Voda Al, Butnaru Gi, Butnaru RC (2020) Enablers of entrepreneurial activity across the european union-an analysis using GEM individual data. Sustain 12:. doi: 10.3390/su12031022

Wang P, Chen K, Zhu S, et al (2020a) Resources, Conservation & Recycling Severe air pollution events not avoided by reduced anthropogenic activities during COVID-19 outbreak. Resour Conserv Recycl 158:104814. doi: 10.1016/j.resconrec.2020.104814
Wang R, Yang Y, Chen R, et al (2015) Knowledge, Attitudes, and Practices (KAP) of the Relationship between Air Pollution and Children’s Respiratory Health in. Int J Environ Res Public Health 12:1834–1848. doi: 10.3390/ijerph120201834

Wang Y, Yuan Y, Wang Q, et al (2020b) Changes in air quality related to the control of coronavirus in China: Implications for traffic and industrial emissions. 731:. doi: 10.1016/j.scitotenv.2020.139133

Yorifuji T, Suzuki E, Kashima S (2014) Hourly differences in air pollution and risk of respiratory disease in the elderly: A time-stratified case-crossover study. Environ Heal A Glob Access Sci Source 13:1–11. doi: 10.1186/1476-069X-13-67

Zambrano-monserrate MA, Alejandra M, Sanchez-alcalde L (2020) Science of the Total Environment Indirect effects of COVID-19 on the environment. Sci Total Environ 728:138813. doi: 10.1016/j.scitotenv.2020.138813

Zhang X, Liu Z, Zhu Y, Zhang K (2020) of Jo ur. doi: 10.1016/j.scitotenv.2020.139282

Zhao H, Che H, Zhang X, et al (2013) Characteristics of visibility and particulate matter (PM) in an urban area of Northeast China. Atmos Pollut Res 4:427–434. doi: 10.5094/APR.2013.049

Zhu G, Guo Q, Xiao H, et al (2017) Multivariate statistical and lead isotopic analyses approach to identify heavy metal sources in topsoil from the industrial zone of Beijing Capital Iron and Steel Factory. Environ Sci Pollut Res 24:14877–14888. doi: 10.1007/s11356-017-9055-9

(2020a) Modes of transmission of virus causing COVID-19: implications for IPC precaution recommendations

(2020b) Tom Tom Traffic Index. https://www.tomtom.com/en_gb/traffic-index/mumbai-traffic/. Accessed 8 May 2020

Figures
Figure 1

a) PM10 level before lockdown, b) PM10 level after lockdown, c) Change in PM10 level, d) PM2.5 level before lockdown, e) PM2.5 level after lockdown, f) Change in PM2.5 level, g) NO2 level before lockdown, h) NO2 level after lockdown, i) Change in NO2 level, j) SO2 level before lockdown, k) PM SO2 level after lockdown, l) Change in SO2 level, m) O3 level before lockdown, n) O3 level after lockdown, o) Change in O3 level, p) AQI before and after lockdown.
Figure 2

(a) Number of days exceeding the permissible limits – PM10  (b) Number of days exceeding the permissible limits – PM2.5
Figure 3

Percentage decrease in pollutant levels based on type of area

Figure 4

Percentage decrease in air quality after lockdown
Percentage decrease in pollutant levels after lockdown in major cities

**Figure 5**

Perception based on residence

(a) Scale of perception with respect to rural/urban

(b) Scale of perception with respect to zones

(c) Scale of perception with respect to major cities

**Figure 6**

Scale of perception
Figure 7

(a) – Perception of air quality before lockdown, (b) – Perception of air quality after lockdown, (c) – Change in perception of air quality

Figure 8

Google trend analysis

Supplementary Files

This is a list of supplementary files associated with this preprint. Click to download.

- supplementarymaterial.docx