

# IMPACT OF COVID-19 PANDEMIC ON THE AIR QUALITY OF INDIA

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## Abstract

Towards the end of 2019, a novel contagious virus (COVID-19) came out of Wuhan, China and turned into a disastrous pandemic. Many countries were locked down; completely or partially. The ongoing pandemic not only affected our economies and routine life, but also the environment. This study was aimed to compare the air quality of the Indian subcontinent prior to and during the COVID-19 pandemic. In this regard, air quality parameters (ozone, nitrogen dioxide, sulfur dioxide, carbon monoxide, PM<sub>2.5</sub> and PM<sub>10</sub>) and meteorological parameters (wind speed and relative humidity) were analysed. The data was obtained from 229 monitoring stations in India and satellite-based Aerosol Absorption Index (AAI) during the springs of 2019 and 2020. The result indicated a significant decline in the concentration mean, six air pollutants (i.e., PM<sub>2.5</sub>, PM<sub>10</sub>, NO<sub>2</sub>, SO<sub>2</sub>, O<sub>3</sub> and CO) decreased by 36.27, 42.96, 44.62, 28.88, 18.35 and 20.51 %, respectively during April 2020 due to less to no industrial activities and vehicular emissions. The spatial variation of each parameter was simulated using the Inverse Distance Weighted (IDW) interpolation method. An Analytical Hierarchy Process (AHP) model was applied to generate the overall air quality severity zonation map of the country. The zonation map indicated that by adopting cleaner fuel and restriction on biomass burning in the rural and urban sectors can improve the ambient air quality.

**Keywords:** Air quality; Analytical Hierarchy Process; COVID-19; India; Inverse Distance Weighted; Spatial interpolation

## Introduction

A novel contagious coronavirus (COVID-19) was diagnosed in Wuhan city of China (Chen *et al.*, 2020) that spread around the globe in the form of a pandemic. According to the World Health Organization (WHO), COVID-19 rapidly spread among humans through respiratory globules in January 2020 (WHO, 2020). In late January 2020, the Chinese Government announced the situation as an epidemic, but subsequently the WHO declared

a worldwide health emergency (Dutheil *et al.*, 2020). In February 2020, COVID-19 cases rose in Italy, Iran, United States, Spain, South Korea, Japan, and United Kingdom. By the end of March 2020, more than half of the world practiced partial or full lockdown (Tosepu *et al.*, 2020; Briz-Redón *et al.*, 2021). There were 11125245 confirmed cases of COVID-19 in June 2020, including 528204 deaths as reported by the WHO (WHO, 2020).

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Due to global lockdown, industrial, manufacturing, and transportation sectors were severely affected. Transportation was the top affected due to the disruption of road and air traffic in order to restrict the local as well as an international movement of people. Air traffic dropped by 96 %; thus, air quality increased due to less carbon emission to the atmosphere (Mostafa *et al.*, 2021).

Urbanization and industrialization is a blessing in disguise as on the one hand it is an indication of development while on the other hand it leads to various environmental issues and one of the major is air pollution. (Weng and Yang, 2004; Somvanshi *et al.*, 2019) PM<sub>10</sub> are inhalable coarse particles with an aerodynamic diameter less than or equal to a nominal 10µm, while PM<sub>2.5</sub> are particles with an aerodynamic diameter less than 2.5µm. In addition to suspended particulate matter (PM<sub>10</sub> and PM<sub>2.5</sub>), ozone (O<sub>3</sub>), oxides of nitrogen, carbon monoxide, and sulphur dioxide are major urban pollutants (Batterman *et al.*, 2007; Wu *et al.*, 2011). The air pollutant concentration is governed by meteorological parameters such as temperature, wind speed and relative humidity and ability of the atmosphere to absorb or disperse the pollutants. The negative correlation of particulate matter with the relative humidity is well known. Even slow wind speed with lower mixing height also affects air pollutant concentration, respective of the monitoring station location (Zaharim *et al.*, 2009; Dominick *et al.*, 2012; Srivastava, 2021). The adverse effect of excessive air pollutants on the human health is well documented (Fann *et al.*, 2012; Cesaroni *et al.*, 2014; Faustini *et al.*, 2014; Raaschou-Nielsen *et al.*, 2015; Greenberg *et al.*, 2016; Khaniabadi *et al.*, 2017; He *et al.*, 2020). According to WHO, on an average, 4.6 million people are dying per year due to poor air quality (Kaya and Kahraman, 2009). From 24<sup>th</sup> March 2020, the Indian government has practiced a severe lockdown over its 1.3 billion residents. Insignificant organizations were deactivated, processing plants were restricted, air traffic throughout the India and abroad were suspended, borders were closed, vehicular travel was stopped and individuals were advised to attempt social distancing to the best. Such restrictions may have long-term economic and behavioural harms under normal situations. However, such Lockdown is the prime non-pharmaceutical aid to break the chain of COVID-19 spreading (Long, 2020).

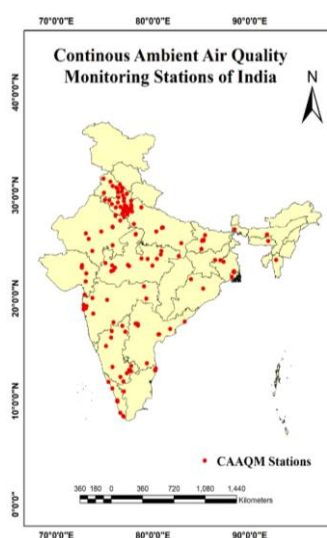
Additionally, these lockdown practices saved many lives (Anderson *et al.*, 2020; Gatto *et al.*, 2020; Gourinchas, 2020; Tobías, 2020). “Is the lockdown good or bad” is the question on the minds of millions. Thus, it is vital to study and

understand the pre- and post-lockdown changes that can lead to the policy making; especially regarding the air quality. In this regard, data of the springs 2019 and 2020 were compared to conclude the effect of lockdown on the India air quality. This study was designed to contemplate, assess and analyse the air quality severity zonation map of the country integrating the variations in the amount of air pollutants, meteorological parameters and AAI using AHP process.

## Materials and Methods

### Ground station data

Central Pollution Control Board (CPCB) is managing various continuous ambient air-quality observing stations in association with local environmental protection agencies throughout India to secure encompassing air quality. They screen 19 air quality and 10 meteorological parameters on the ground. The information from these destinations incorporates mass concentrations and 24 hours mean concentrations (daily mean). For the present study, hourly measurements of all the selected air pollutants (PM<sub>2.5</sub>, PM<sub>10</sub>, NO<sub>2</sub>, SO<sub>2</sub>, Ozone, CO, and meteorological parameters governing pollutant concentration (wind speed (WS) and relative humidity (RH)) were collected from 229 sites (Figure 1). The obtained data primarily belongs to the official website of central control room for air quality management managed by central pollution control board (CPCB). The data spanned two periods: Period 1) 1<sup>st</sup> March - 30<sup>th</sup> April 2019; Period 2) 1<sup>st</sup> March - 30<sup>th</sup> April 2020.



**Figure 1. Continuous Ambient Air Quality Monitoring Stations of CPCB in India**

**Table 1. Definition of Numerical Scales for Pair-Wise Comparison (T.L. Saaty, 1977)**

| Scale       | Degree of preference | Remarks                                     |
|-------------|----------------------|---------------------------------------------|
| 1           | Equally              | Factors inherit equal contribution          |
| 3           | Moderately           | One factor moderately favored over other    |
| 5           | Strongly             | Judgement strongly favor one over other     |
| 7           | Very strongly        | One factor very strongly favored over other |
| 9           | Extremely            | One factor favored over other in highest    |
| 2, 4, 6, 8  | Intermediate         | Compensation between weights 1,3,5,7 and 9  |
| Reciprocals | Opposite             | Refers inverse comparison                   |

estimations of a continuous variable distributed in time at un-sampled areas or space. Inverse Distance Weighted (IDW) is one of such techniques, which presumes that close moieties are more effective than progressively far off isolated ones (Sathe *et al.*, 2021). To anticipate a value for any unmeasured territory, IDW utilizes the measured values encompassing the forecast area. It gives more prominent weights to points closest toward the forecast zone, and the weights diminish as a function of separation) (Sree Dhevi, 2015). IDW was applied to determine spatial pattern and distribution of all the nine parameters over the entire country.

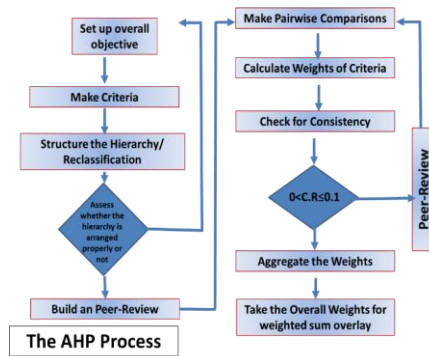
### Analytical Hierarchy Process (AHP)

AHP is a strategy that provides weights to various criteria. AHP was implemented on the IDW interpolated maps. AHP is required to reveal the severity of air quality before and during lockdown. Also, it generates the overall air quality severity zone maps for both the time period. In the present study, weights were provided to all the nine criteria (PM<sub>2.5</sub>, PM<sub>10</sub>, NO<sub>2</sub>, O<sub>3</sub>, SO<sub>2</sub>, CO, WS, RH and AAI) using Easy AHP module of QGIS 2.18. AHP is a productive technique that connects quantitative and qualitative parameters through the user's assessment and is able to assess the errors in decisions with precise outcomes (Somvanshi *et al.*, 2020). The advantage of AHP lies on the formation of a chain of 'pairwise comparison' matrices that compare all the criteria and provide weights, which express the significance of the criteria in contributing to the overall objective. This technique was implemented in three prominent steps: (a) generation of pairwise comparison matrix; (b) computation of criterion weights; and (c) estimation of consistency ratio. The AHP procedure is presented in Figure 2.

Pairwise comparison matrix comprises designated weights of criteria and alternatives on a nine point ordinal scale by virtue (Table 1) of pairwise comparison amongst them (Saaty, 1977). The nine criteria were compared pairwise while weights were allocated with every one of the criteria on a scale (1-9) depending on their comparative significance with respect to each other in causing a prominent effect on the ambient air.

The estimated factor weights can be subjective once in a while; henceforth to evade such a case, the consistency of the comparison matrix is indicated through consistency ratio (CR), which is expressed as the proportion of consistency index (CI) and random index (RI).

RI was created by Saaty (1980) by considering numerous arbitrary examples. It is the index of a randomly created pairwise comparison matrix. CI is expressed in equation. 1.

**Figure 2. AHP Process**

### Sentinel – 5P TROPOMI data

The Aerosol Absorption Index (AAI) is a qualitative index demonstrating increased layers of aerosols with significant absorption (*Aerosol Index - Level-2 Processing - Sentinel-5P Technical Guide - Sentinel Online*). The aerosol layer in atmosphere primarily consists of airborne matter such as desert dust, biomass burning and volcanic debris tufts. The advantage of AAI is that it can estimate concentration of aerosol over the satellite image with clear sky or having cloud cover.

The TROPOMI aerosol index retrieves AAI for two sets of wavelengths in the spectral band three: 340/380 nm; the pair of wavelengths utilized by most instruments retrieving AAI. AAI data of the entire country was collected from sentinel official website (*Sentinel-5P Pre-Operations Data Hub*) for the time periods stated in the previous section.

### Spatial Analysis

Spatial analysis is generally carried out to understand topology, geometry and geography of a location. One of the explanatory methods of spatial analysis in Geo-statistics is spatial interpolation. It analyses the spatial patterns and computes the

$$CI = \lambda_{\max} - n/n - 1 \quad (1)$$

where,  $\lambda_{\max}$  is the highest eigenvalue of the matrix while  $n$  is the number of factors (here,  $n = 9$ ).

According to Saaty, a CR value  $< 0.1$  may provide inconsistent dependable while CR = 0 means a consistent judgment that is free of error. The pairwise comparison matrix was further used to calculate weighted linear combination (T. Saaty, 1980; Ramanathan, 2001; Saaty Thomas and Thomas, 2006).

Interpolated maps (PM<sub>2.5</sub>, PM<sub>10</sub>, NO<sub>2</sub>, Ozone, SO<sub>2</sub>, CO, WS, RH, and AAI) were integrated into ARCGIS 10.5 to distinguish and map the air quality severity zones with respect to pollutant's concentration. The weights determined using AHP were allocated to every criterion. Attributes were scored from 1 to 5 (1: best air quality, 5: poor air quality).

## Results and Discussions

Air quality and meteorological parameters studied in India were Temporally analysed (Table 2).

Overall average concentration of all air pollutants sharply declined in both March and April of 2020 as compared to the previous year. The data were interpolated to understand the spatial distribution of pollutant and meteorological parameters. The comparison of data belongs to 2019 and 2020 showed that main pollutants (PM<sub>2.5</sub>, PM<sub>10</sub>, NO<sub>2</sub>, SO<sub>2</sub>, O<sub>3</sub> and CO) reduced in the air after lockdown. On the other hand, meteorological parameters and AAI irregularly changed.

Due to the largest global lockdown, most of the processing plants, markets, and places of worship are currently closed. Public transport is suspended and construction is halted. The Government of India has requested its residents to stay at home and practice social distancing. The fundamental urban communities are witnessing huge dip in the concentration of harmful microscopic particulate matter known as PM<sub>2.5</sub>. PM<sub>2.5</sub> poses high health risks as it can hold up profoundly into the respiratory system and can reach to different organs via the circulation system. The spatial map also depicts that in Delhi, the capital of India, and some of the cities of Uttar Pradesh, the mean of PM<sub>2.5</sub> concentration plunged after the lockdown began (Figure 3(a)). Recently, Wang *et al.* (2020) have analyses PM<sub>2.5</sub> data in Beijing, Shanghai, Guangzhou, and Wuhan cities during COVID-19 and found a pronounced reduction in the atmospheric pollution that can be attributed to the reduction of transport and industrial emissions. The PM<sub>10</sub> concentration dropped by

36.27 % during the nationwide curfew in April 2020 (Figure 3(b)). In cities like Delhi and Mumbai, a decline of 35 and 14 % was observed as compared to March 2019. Similar changes were also observed in Beijing and Shanghai cities of China (Chauhan and Singh, 2020)

Suspended street residue and construction-based dust are the main PM<sub>10</sub> imitators. With constrained traffic, street dust is reduced. Overall PM<sub>10</sub> dropped down to the least; monthly mean of 68.94  $\mu\text{g}/\text{m}^3$  in April 2020. However, dust storms originating from the western region in April 2019 rapidly raised the monthly mean concentration to 123.21  $\mu\text{g}/\text{m}^3$ . Similar western dust storm was also observed in March 2020.

CO has the longest tropospheric lifetime of roughly two months, due to which, it does not vary swiftly. Despite the fact that there is a general decline in CO concentration across the country, it is still insignificant (Figure 3(c)).

Less traffic and power plant operations also decreased the release of nitrogen oxides (NO<sub>x</sub>) to the atmosphere (Falocchi *et al.*, 2021). During the months of March and April, the mean NO<sub>2</sub> level declined in various regions of India like Mumbai, Pune, Chennai, Kolkata, Bengaluru and Ahmedabad, compared to the same month in 2019. The high NO<sub>2</sub> concentration was observed over north-eastern part of India in 2019 that can be directly linked to the locations of ongoing coal-based power plants (Figure 3(d)).

The sulphur dioxide (SO<sub>2</sub>) is the main contaminant that consistently complied with the national standards. In most of the significant Indian urban communities, there is no perceivable distinction between its concentration during the lockdown. The chief sources of SO<sub>2</sub> emissions are diesel and coal. Many of the cities as per Government orders, already have access to BS-6 fuel; having least sulphur content. There are other aspects in lined with the reduced vehicular movement like shutdown of industries and power plants. As per the interpolated maps of March – April 2019, SO<sub>2</sub> concentration was a bit high (monthly mean: 14.54 and 13.85  $\mu\text{g}/\text{m}^3$ , respectively) as certain power plants industries were on production. The stated values comparatively reduced (monthly mean: 9.85  $\mu\text{g}/\text{m}^3$ ) after lockdown with in the month of April 2020. Overall, there was a decline in the SO<sub>2</sub> concentration by 28.88 % nationwide. The SO<sub>2</sub> concentration always remains within the permissible limits throughout the year nationwide (Figure 3(e)).

Ozone (O<sub>3</sub>) is the only secondary pollutant on this list of air contaminants. Ozone is framed and destroyed within the sight of nitrogen oxides (NO<sub>x</sub>) and volatile organic compounds (VOCs). The

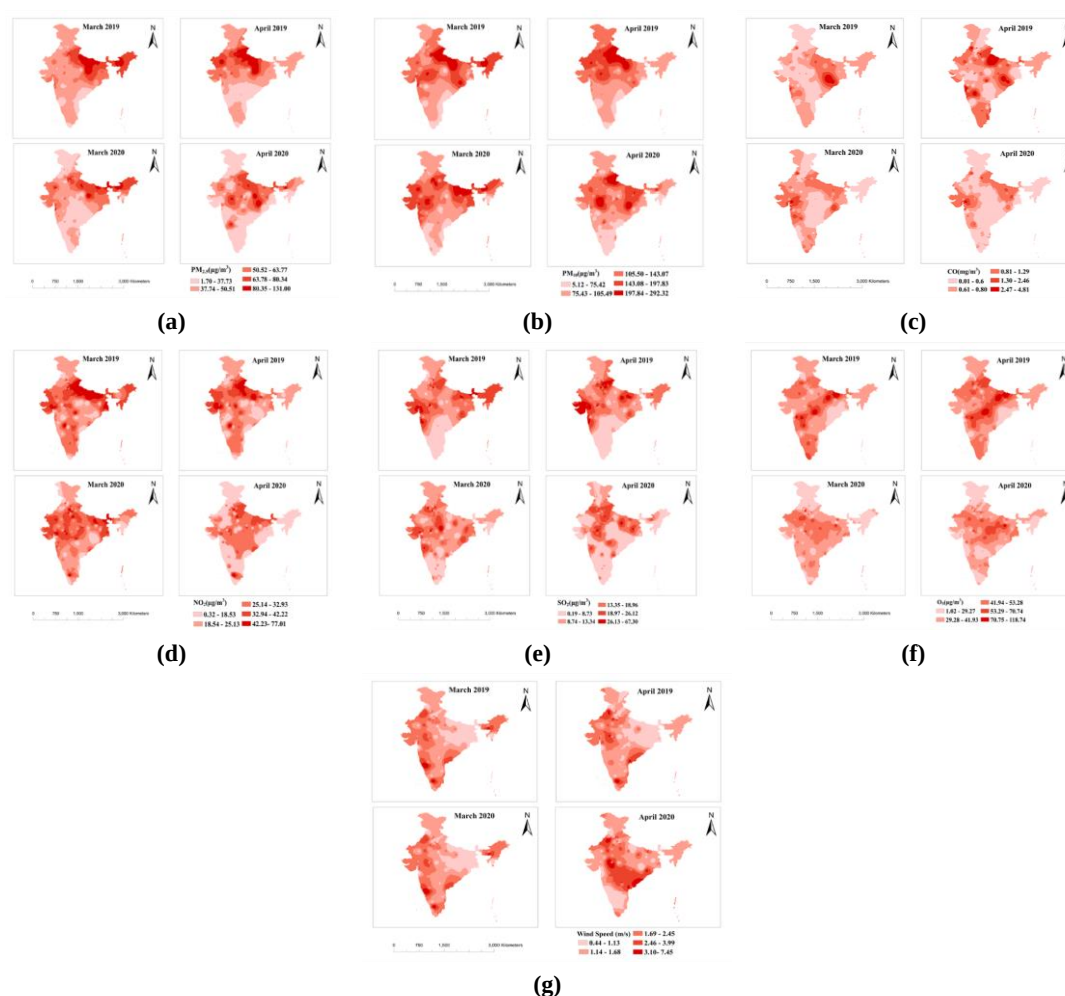
growth of  $O_3$  is usual during spring and summer owing to higher solar radiation (in terms of intensity and daily duration), which promotes the photolysis of  $NO_2$  (Escudero *et al.*, 2019).

The monthly mean of  $O_3$  concentration in the months of March and April 2019 was 41.59 and 43.47  $\mu g/m^3$ , respectively. Whereas during the lockdown, it has reduced considerably to 34.87 and 35.49  $\mu g/m^3$  for the months of March and April 2020, respectively; still a minor change that may be attributed to the chemistry associated with the

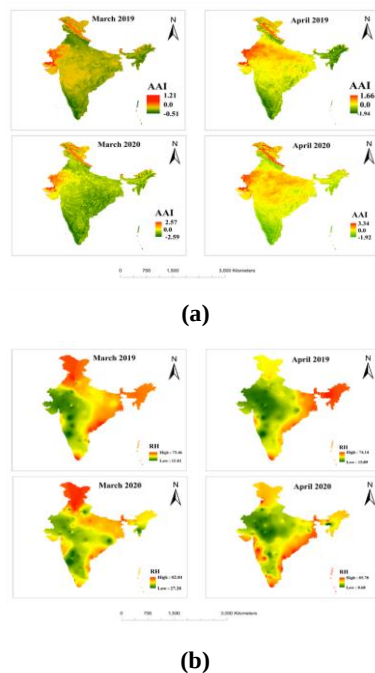
tropospheric ozone.  $NO_x$  consists of  $NO$  and  $NO_2$ .  $NO$  destroys ozone while  $NO_2$  accelerates its formation. Transportation is one of the major sources of the  $NO_x$  emission in the country. Lockdown limited  $NO$  and  $NO_2$  production, which on one hand reduced ozone formation due to the decline in the  $NO_2$  concentration, while on the other hand saved ozone from destruction. Therefore, change in ozone amount in the atmosphere was insignificant throughout the country during the lockdown period (Figure 3(f)).

**Table 2. The mean change of nine criteria in each year of the study area month-wise**

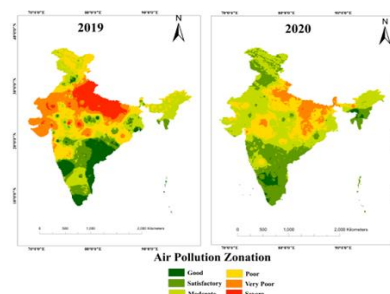
| Month/Year | PM <sub>2.5</sub><br>( $\mu g/m^3$ ) | PM <sub>10</sub><br>( $\mu g/m^3$ ) | NO <sub>2</sub><br>( $\mu g/m^3$ ) | SO <sub>2</sub><br>( $\mu g/m^3$ ) | O <sub>3</sub><br>( $\mu g/m^3$ ) | CO<br>(mg/m <sup>3</sup> ) | WS<br>(m/s) | RH<br>(%) | AAI   |
|------------|--------------------------------------|-------------------------------------|------------------------------------|------------------------------------|-----------------------------------|----------------------------|-------------|-----------|-------|
| March 2019 | 57.53                                | 123.21                              | 28.77                              | 14.54                              | 41.59                             | 0.86                       | 1.62        | 48.93     | -0.70 |
| March 2020 | 38.91                                | 85.59                               | 21.61                              | 12.95                              | 34.87                             | 0.73                       | 1.41        | 55.72     | -1.24 |
| April 2019 | 50.92                                | 120.87                              | 26.58                              | 13.85                              | 43.47                             | 0.78                       | 1.45        | 44.12     | -0.55 |
| April 2020 | 32.45                                | 68.94                               | 14.72                              | 9.85                               | 35.49                             | 0.62                       | 1.57        | 45.75     | -0.88 |



**Figure 3. Spatial Distribution of Air Pollutants and Parameters (a) PM<sub>2.5</sub> (b) PM<sub>10</sub> (c) CO (d) NO<sub>2</sub> (e) SO<sub>2</sub> (f) Ozone (g) Wind Speed**



**Figure 4. Spatial Distribution (a) Relative Humidity (b) Aerosol Absorption Index**



**Figure 5. Air Quality Severity Zonation Maps for the year 2019 and 2020**

There were less variations in the wind speed and relative humidity over the country during the lockdown (Figure 4), whereas Indian meteorologists were suggesting a notable impact on the weather after the nationwide lockdown. The meteorological aspect is essential in the sense that weather has a massive influence on air quality (Demuzere *et al.*, 2009; Jhun *et al.*, 2015; Baklanov *et al.*, 2016; Borge *et al.*, 2019; Zhao *et al.*, 2019). The drop in pollution concentration may have an effect on temperatures, particularly nocturnal, and brought intense pre-monsoon showers in the month of April 2020.

Aerosols derived from vehicles and processing plants enormously add to the air contamination. Aerosols are one of the main contaminants throughout the country's air, particularly in urban

regions. Smaller aerosols released through anthropogenic activities can be more damaging to human health as compared to the natural larger ones originated from dust storms or forest fires. Decrease of aerosols in the air during March 2020 might be a little silver coating in the midst of this worldwide pandemic; whether the impact is permanent or temporary (Figure 4(b)). Weather and winds have a serious impact on the aerosol concentration in the lower atmosphere. So, it is difficult to say how much of what, that is observed, comes from anthropogenic activities and how much is related to the lockdown.

Air Quality Maps using Analytical Hierarchy Process (AHP)

The air quality severity zonation map was prepared considering different parameters. Each parameter considered for air quality assessment in this study has its variations within it in expressing the severity that needs to be given specific ratings. The weighted sum overlay approach built into Arc Map Spatial Analyst is adapted for integration of input data layers where the data layers are multiplied by their corresponding weights obtained from Saaty's pair-wise comparison matrix, and the same were summed up together to achieve the air quality severity zonation map.

Thus, the final output of the analysis comes out in the form of air quality severity zonation map showing six zones with zones one to six indicating the good, satisfactory, moderate, poor, very poor and severe zones respectively.

Considering the factors accelerating air pollution severity pairwise comparison was performed. The pairwise comparison matrix is presented in Table 3 and 4. The diagonal value in the table indicates comparison between the criteria of equal importance while off diagonal values show the importance of one criterion over the other. Using this method, all possible ways of comparing the criteria was done and CR was estimated. The value of CR specifies the level of consistency in the pairwise comparisons. CR less than 0.10, indicates a reasonable level of consistency. The Consistency ratio obtained for 2019 and 2020 was 0.075 and 0.083 respectively.

Once the CR was estimated the weights for each parameter were assigned (Table 5). The highest weights for the years 2019 and 2020 were assigned to PM<sub>10</sub> (0.205) and PM<sub>2.5</sub> (0.212), respectively where the least weights were assigned to WS (0.058) and CO (0.05). The Air quality severity zonation maps, showing comparative changes in overall air quality of the country in April 2019 and 2020, respectively, were generated by overlaying different interpolated maps (PM<sub>2.5</sub>, PM<sub>10</sub>, NO<sub>2</sub>, O<sub>3</sub>, SO<sub>2</sub>, CO, WS, RH and AAI) using GIS integration.

**Table 3. Pair wise Comparison Matrix for April 2019**

|                   | RH    | CO    | O <sub>3</sub> | NO <sub>2</sub> | AAI   | PM <sub>10</sub> | SO <sub>2</sub> | WD    | PM <sub>2.5</sub> |
|-------------------|-------|-------|----------------|-----------------|-------|------------------|-----------------|-------|-------------------|
| RH                | 1     | 0.556 | 0.588          | 0.688           | 0.526 | 0.667            | 0.388           | 0.667 | 0.435             |
| CO                | 1.8   | 1     | 0.625          | 0.286           | 0.947 | 0.5              | 0.323           | 0.37  | 0.332             |
| O <sub>3</sub>    | 1.7   | 1.6   | 1              | 5               | 1.042 | 0.556            | 0.498           | 0.303 | 0.45              |
| NO <sub>2</sub>   | 1.453 | 3.5   | 0.2            | 1               | 0.556 | 0.689            | 0.556           | 0.5   | 0.5               |
| AAI               | 1.9   | 1.056 | 0.96           | 1.8             | 1     | 0.323            | 0.435           | 0.323 | 0.286             |
| PM <sub>10</sub>  | 1.5   | 2     | 1.8            | 1.452           | 3.1   | 1                | 1               | 0.625 | 0.5               |
| SO <sub>2</sub>   | 2.58  | 3.1   | 2.01           | 1.8             | 2.3   | 1.6              | 1               | 0.332 | 0.506             |
| WD                | 1.5   | 2.7   | 3.3            | 2               | 3.1   | 1.6              | 3.012           | 1     | 1.667             |
| PM <sub>2.5</sub> | 2.3   | 3.01  | 2.22           | 2               | 3.5   | 2                | 1.978           | 0.6   | 1                 |

**Table 4. Pair wise Comparison Matrix for April 2020**

|                   | PM <sub>10</sub> | PM <sub>2.5</sub> | NO <sub>2</sub> | O <sub>3</sub> | WD    | CO    | RH    | AAI   | SO <sub>2</sub> |
|-------------------|------------------|-------------------|-----------------|----------------|-------|-------|-------|-------|-----------------|
| PM <sub>10</sub>  | 1                | 0.667             | 0.417           | 1.038          | 0.333 | 0.714 | 0.549 | 0.25  | 0.304           |
| PM <sub>2.5</sub> | 1.5              | 1                 | 0.909           | 0.2            | 0.947 | 0.331 | 0.323 | 0.288 | 0.332           |
| NO <sub>2</sub>   | 2.4              | 1.1               | 1               | 1.25           | 1.042 | 0.556 | 0.498 | 0.2   | 0.417           |
| O <sub>3</sub>    | 0.963            | 5.01              | 0.              | 1              | 1.053 | 0.689 | 0.556 | 0.801 | 0.375           |
| WD                | 3                | 1.056             | 0.96            | 0.95           | 1     | 0.263 | 0.476 | 1     | 0.328           |
| CO                | 1.4              | 3.025             | 1.8             | 1.452          | 3.8   | 1     | 0.33  | 0.5   | 0.658           |
| RH                | 1.821            | 3.1               | 2.01            | 1.8            | 2.1   | 3.03  | 1     | 0.238 | 0.503           |
| AAI               | 4                | 3.47              | 5               | 1.249          | 1     | 2     | 4.2   | 1     | 1.111           |
| SO <sub>2</sub>   | 3.291            | 3.01              | 2.4             | 2.67           | 3.05  | 1.52  | 1.987 | 0.9   | 1               |

**Table 5. Pair wise Comparison Matrix for April 2020**

| S.No. | Index Name        | Weights    |            |
|-------|-------------------|------------|------------|
|       |                   | April 2019 | April 2020 |
| 1     | PM <sub>2.5</sub> | 0.07       | 0.212      |
| 2     | PM <sub>10</sub>  | 0.205      | 0.135      |
| 4     | NO <sub>2</sub>   | 0.133      | 0.083      |
| 5     | SO <sub>2</sub>   | 0.175      | 0.072      |
| 6     | O <sub>3</sub>    | 0.101      | 0.094      |
| 7     | CO                | 0.115      | 0.05       |
| 9     | WS                | 0.058      | 0.051      |
| 10    | RH                | 0.061      | 0.12       |
| 12    | AAI               | 0.081      | 0.181      |

Comparison of the air quality severity zonation maps (Figure 5) for 2019 and 2020 (March - April) concludes that most of the northern part of the country has less severe and poor air quality in year 2019. Whereas, this severity can be hardly seen nationwide in 2020 (March - April) due to lockdown. Reduction in air pollution concentration resulted in smoother and good quality air. The results shown here anticipate what the air quality in cities would look like if the world switched to a low-carbon economy, leading also to climate co-benefits. They can be used as a foundation to develop more stringent regulations to decrease the exposure of the urban population to air pollutants as reported earlier (Krecl *et al.*, 2020)

## Conclusions

The current Covid-19 pandemic-initiated scenario is evidence of the fact that highly dense urban areas

and non-toxic air quality can be achieved quite swiftly if strict and firm steps are taken to lower the burning of fossil fuels. COVID-19 pandemic has posed a genuine risk to many businesses, government organizations, and especially to human health. However, it has also brought to our consensus that the environment has restoration ability. Due to the travel restrictions and less industrial activity during this pandemic, on mean, six air pollutants (i.e., PM<sub>2.5</sub>, PM<sub>10</sub>, NO<sub>2</sub>, SO<sub>2</sub>, O<sub>3</sub> and CO) decreased by 36.27, 42.96, 44.62, 28.88, 18.35 and 20.51 %, respectively during April 2020. The air become cleaner on the price of human sufferings and deaths and has taught us a lesson to protect our future. Control on emission of the certain key anthropogenic pollutants and use of cleaner fuel may improve the ambient air quality. Both government and civilians must gain insights from this lockdown and make policies and strategies to reduce carbon monoxide, NO<sub>x</sub> and SO<sub>x</sub> emissions.

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