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Status of Air Pollution during COVID-19-Induced Lockdown in Delhi, India

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Abstract: To monitor the spread of the novel coronavirus (COVID-19), India, during the last week of March 2020, imposed national restrictions on the movement of its citizens (lockdown). Although India's economy was shut down due to restrictions, the nation observed a sharp decline in particulate matter (PM) concentrations. In recent years, Delhi has experienced rapid economic growth, leading to pollution, especially in urban and industrial areas. In this paper, we explored the linkages between air quality and the nationwide lockdown of the city of Delhi using a geographic information system (GIS)-based approach. Data from 37 stations were monitored from 12 March, 2020 to 2 April, 2020 and it was found that the Air Quality Index for the city was almost reduced by 37% and 46% concerning $PM_{2.5}$ and PM10, respectively. The study highlights that, in regular conditions, the atmosphere's natural healing rate against anthropogenic activities is lower, as indicated by a higher AQI. However, during the lockdown, this sudden cessation of anthropogenic activities leads to a period in which the natural healing rate is greater than the induced disturbances, resulting in a lower AQI, and thus proving that this pandemic has given a small window for the environment to breathe and helped the districts of Delhi to recover from serious issues related to bad air quality. If such healing windows are incorporated into policy and decision-making, these can prove to be effective measures for controlling air pollution in heavily polluted regions of the World.

Keywords: air quality index (AQI); COVID-19; lockdown; $PM_{2.5}$; PM10; interpolation of AQ parameters; satellite remote sensing; GIS

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1. Introduction

Air pollution is a major concern worldwide; according to the World Health Organization (WHO) survey, 14 out of 15 of India's most polluted cities have been affected. Air pollution, particularly in megacities, has an unfavorable impact on daily human life. Delhi has experienced rapid economic growth in recent years, which has led to pollution, especially in urban and industrial areas. In Delhi, the main contributors to PM10 contaminants are road dust (56%), concrete batching (10%), industrial-level sources (10%), and automobiles (9%) [1]. Air quality management in urban environments is required to safeguard human health, reduce industrial losses, maximize workers' productivity, and enhance indoor air quality. In this regard, air quality monitoring, networks of Continuous Air Quality Monitoring (CAQM) stations, satellite datasets, and geographic information system (GIS) technology play a crucial role.

In India, since 1974, the Central Pollution Control Board (CPCB) has been responsible for air quality monitoring [2]. In major cities, networks were developed for air quality calculations. CPCB and other state pollution control boards currently maintain and manage a network of 133 ground stations, Continuous Air Quality Monitoring Stations (CAQM), and 37 CAQM stations within the Delhi area. The Government of Delhi has sought to regulate air pollution through vehicle enforcement laws such as the odd-even formula, the prohibition of 10-year-old diesel vehicles, the introduction of Compressed Natural Gas (CNG) vehicles, public incentives for carpooling, etc. Delhi's major contaminants in the atmosphere are particulate matter ($PM_{2.5}$ and PM10), nitrogen oxides, sulfur dioxide, carbon monoxide, ozone, benzene, toluene, xylene, carbonaceous and organic aerosols, metals, and volatile organic compounds [3]. The research published in May 2014 by the WHO used datasets from 2008–2013 and ranked Delhi as the most polluted city in the World, with an average yearly $PM_{2.5}$ concentration of 153 $\mu g/m^3$.

Many studies have been performed earlier on GIS techniques to track air pollution. This technology provides a detailed overview of the city, identifies the significant sources of pollution and the distribution pattern, helps decide where to make efforts to reduce pollution rates, and agrees on any relation between city characteristics and air pollution distribution. A GIS-based methodology has been established [4–7] and is increasingly utilized in the natural environment's measurement, analysis, perception, simulation, and management [8–12]. The statistical interpolation process also uses GIS to create 'virtual stations' [13]. In light of this, on 14 April 2020, the Government of India extended the lockdown that had been put in place on 24 March, 2020 until 3 May, 2020. This action was taken to combat the virus's lethality through social isolation and other measures, as recommended by the WHO [14]. India has developed a far-reaching strategy to address the pandemic and its economic woes properly. Zoning the COVID-19 epicenters is one such method. The federal government and the individual states are dividing the country into zones of varying danger; the zone with the greatest number of confirmed cases will be quarantined for a lengthy period of time [10].

During the first week of February 2020, the novel coronavirus (COVID-19) epidemic broke out in India. After monitoring its propagation, India imposed a nationwide lockdown from 24 March, 2020, leading to major declines in economic activities and related emissions. Although India's economy was shut down to prevent COVID-19 from spreading, the nation observed a sharp decrease in particulate matter. Many researchers carried out the study of lockdown impact on air pollution in the Delhi and other cities of India [15–18] and have reported a reduction of AQI in the range of 30–50% and 40–60% for NOx.

Air quality assessment is carried out in Delhi based on ground measurements of 37 CAQM stations throughout this paper. The study highlights the impact of the lockdown on air quality standards due to an outbreak of Severe Acute Respiratory Syndrome Coronavirus 2 (SARS-CoV-2). The observation period of this study is taken from 12 March to 2 April 2020. The study further aims to show the potential of GIS in monitoring the Air Quality spatial distribution, mapping it on a microscale level, and analyzing the particulate matter concentrations of the Delhi region. Moreover, this research also hopes to demonstrate the potential rate of nature's ability to heal from anthropogenic activities.

2. Materials and Methods

2.1. Study Area

Delhi is the capital of India and is also the country's economic capital. Delhi is the most densely populated city in the country and the World. Delhi city has an area of approx. 1490 sq. km and extending between north latitudes 28°25′ and 28°55′ and east longitudes 76°45′ and 78°20′. It is surrounded on three sides by Haryana and on the east by Uttar Pradesh. According to the 2011 census, the population of Delhi was more than 11 million [19], India's second-largest city after Mumbai, while the overall NCT city was around 16.8 million. Delhi has a subtropical humid dry-winter climate bordering a hot semi-arid climate. The warm season occurs between 21 March and 15 June, with a daily average high temperature of 39 °C (102 °F). The coldest day of the year is 4 January, between the mean of 2 °C (36 °F) and 14 °C (57 °F). The wind moves from the northwest to the southwest in early March. The selection of this study area is attributed to dramatic environmental changes due to the nationwide lockdown and the availability of air quality data for CAQM stations. The study area map is shown in Figure 1.

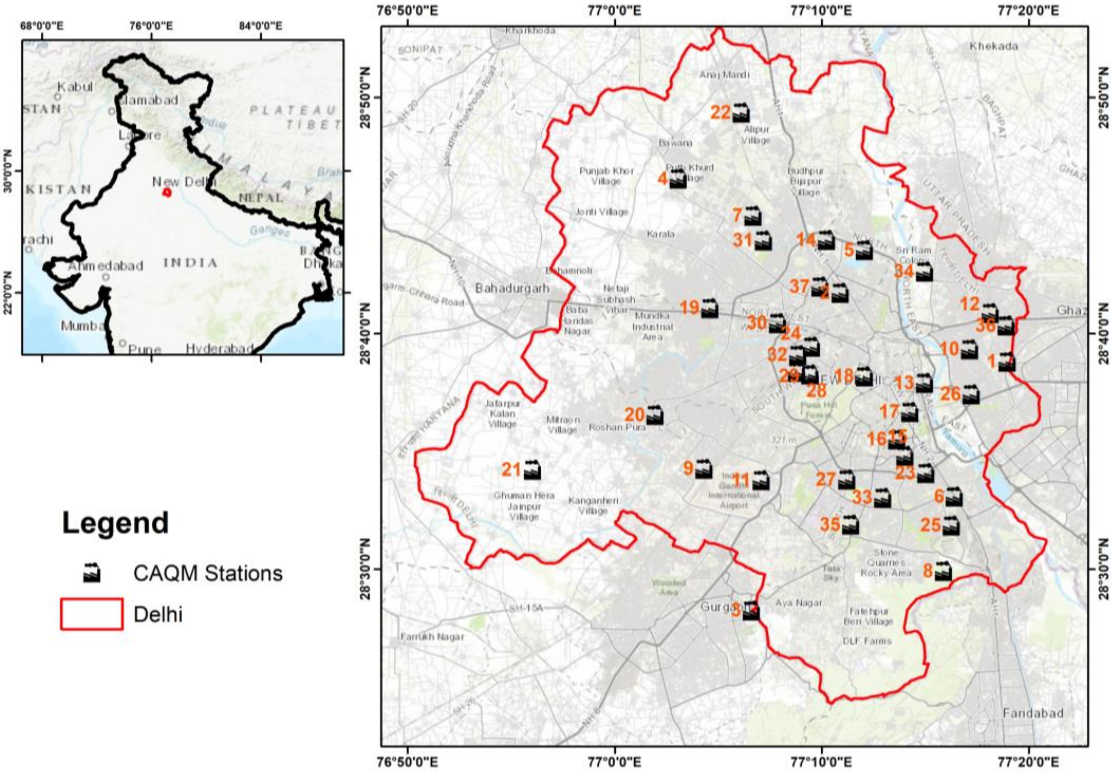

Figure 1. The study area map depicting the CAQM stations. The distribution of the 37 CAQM stations is shown on the map.

The methodology employed to assess the Air Quality parameters includes Data Acquisition from Delhi CAQM stations, Data Processing and Data Analysis. The Data Processing portion consists of converting all non-spatial data into spatial data. After conversion, spatial data was used for geospatial mapping of various pollutants, viz. PM10 and $PM_{2.5}$. In the Data Analysis part, an error assessment of various interpolation techniques was performed, and the best interpolation technique was chosen. Then, the Air Quality Index was evaluated using the linear interpolation technique provided by the Environmental Protection Agency (EPA) [20]. The other processed result was analyzed to determine the variation in air pollution before and during the nationwide lockdown period. The period was chosen so that the effect of rainfall is minimal. The image below shows the rainfall in the pre- and during-lockdown period (Figures 2 and 3).

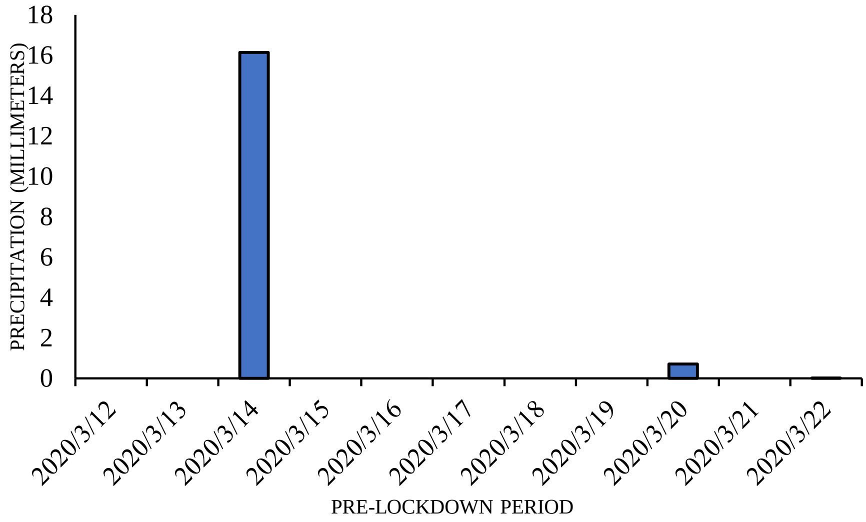

Figure 2. Rainfall in the pre-lockdown period.

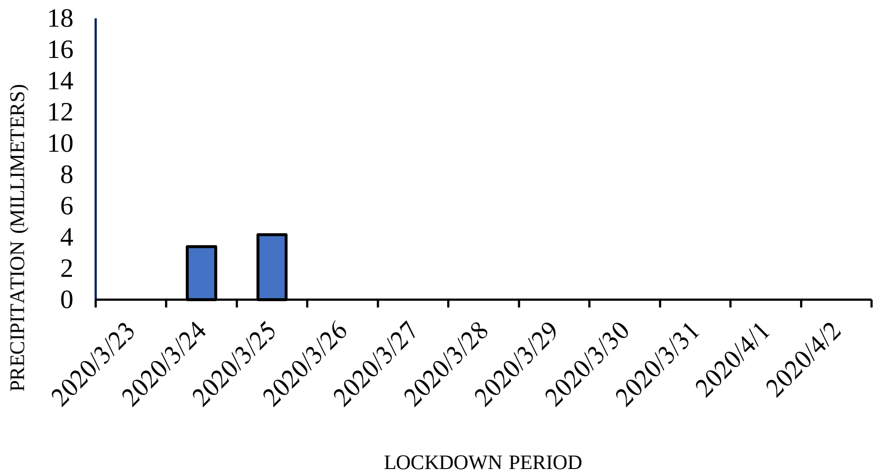

Figure 3. Rainfall during the lockdown period.

It can be observed that during the pre-lockdown period, only one rainfall event took place, on 14 March, 2020, measuring around 16 mm. During the lockdown period (23 March 2020, to 2 April, 2022), only two precipitation events occurred in the study area that too, on the first two days of lockdown (i.e., on 23 and 24 March 2022), with an average precipitation of a meager 3.74 mm as shown in Figures 2 and 3. This rules out any possibility of the influence of rain on the washing of atmospheric PM before and during the lockdown period. Using this study, we intended to show how the atmosphere gets influenced due to anthropogenic activities in the capital of India, New Delhi, considered the second most polluted city in the World. COVID-19, although it had its negative impacts on the human systems, it did show that if the human influence on the environment is reduced, the environment has an inbuilt mechanism to recover to its original state.

Wind can play a major role in concentrating the $PM_{2.5}$ and PM10 in the atmosphere. However, it must be noted that Delhi is completely surrounded by industries on all sides. Under normal circumstances, winds act as the force for concentrating the PM in the Delhi region. Since the industries were shut down during the lockdown period, the lockdown provided the best opportunity to study their influence on the air quality index during the no-work (lockdown) period. The particulate matter due to industries was also reduced during the lockdown period. Therefore, this period was the best period for assessing the role of anthropogenic activities on atmospheric particulate matter.

2.2. Data Acquisition

The first step includes the processing of data. Data used in this study are from 37 CAQM stations (Table 1), air pollutants, and GIS data. The air pollution data consists of two (2) pollutant components ($PM_{2.5}$ and PM10) between 12 March, 2020, and 2 April, 2020. The date range for the study was split into two sections. One is the average from 12 March, 2020, to 22 March, 2020 (before lockdown) and the other from 23 March, 2020, to 2 April, 2020. The GIS dataset includes the administrative boundary of Delhi districts and locations of CAQM stations in the study area. The adopted methodology flow chart is shown in Figure 4.

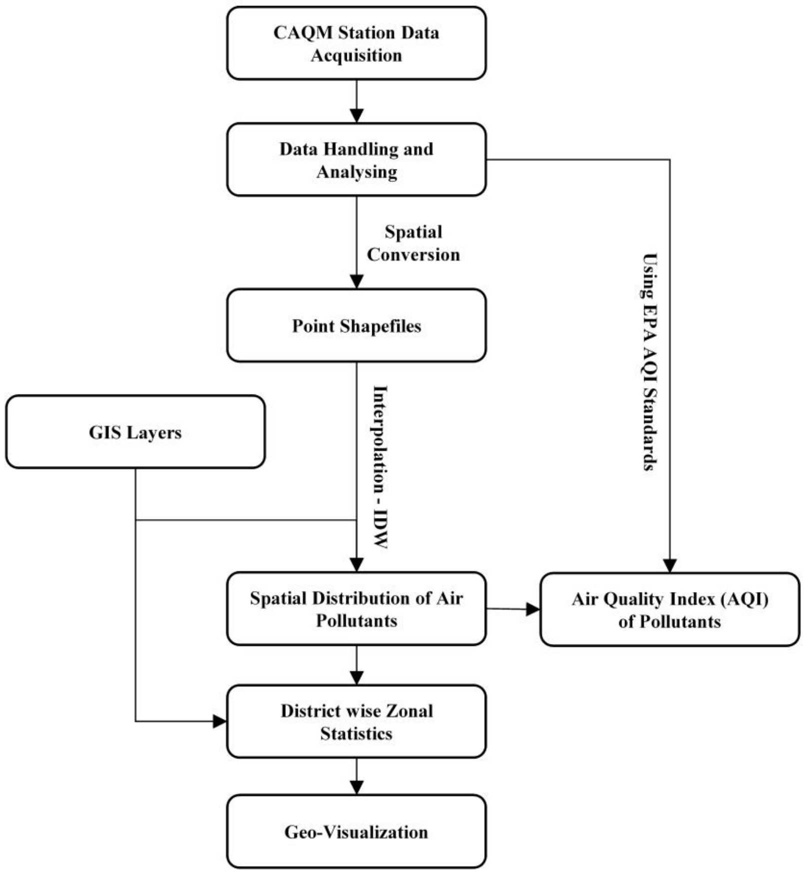

Figure 4. The overall methodology used in this study.

Table 1. List of Continuous Air Quality Monitoring Stations (CAQM) stations maintained by the Central Pollution Control Board (CPCB), Delhi Pollution Control Committee (DPCC), and India Meteorological Department (IMD).

Sl. No.	Station Name	Sl. No.	Station Name
1	Anand Vihar, Delhi-DPCC	20	NSIT Dwarka, New Delhi-CPCB
2	Ashok Vihar, Delhi-DPCC	21	Najafgarh, Delhi-DPCC
3	Aya Nagar, New Delhi-IMD	22	Narela, Delhi-DPCC
4	Bawana, Delhi-DPCC	23	Nehru Nagar, Delhi-DPCC
5	Burari Crossing, New Delhi-IMD	24	North Campus, DU, New Delhi-IMD
6	CRRI Mathura Road, New Delhi-IMD	25	Okhla Phase-2, Delhi-DPCC
7	DTU, New Delhi-CPCB	26	Patparganj, Delhi-DPCC

Table 1. *Cont.*

Sl. No.	Station Name	Sl. No.	Station Name
8	Dr Karni Singh Shooting Range, Delhi-DPCC	27	Punjabi Bagh, Delhi-DPCC
9	Dwarka-Sector 8, Delhi-DPCC	28	Pusa, Delhi-DPCC
10	East Arjun Nagar, Delhi-CPCB	29	Pusa, New Delhi-IMD
11	IGI Airport (T3), New Delhi-IMD	30	R K Puram, New Delhi-DPCC
12	IHBAS, Dilshad Garden, New Delhi-CPCB	31	Rohini, Delhi-DPCC
13	ITO, New Delhi-CPCB	32	Shadipur, New Delhi-CPCB
14	Jahangirpuri, Delhi-DPCC	33	Sirifort, New Delhi-CPCB
15	Jawaharlal Nehru Stadium, Delhi-DPCC	34	Sonia Vihar, Delhi-DPCC
16	Lodhi Road, New Delhi-IMD	35	Sri Aurobindo Marg, Delhi-DPCC
17	Major Dhyan Chand National Stadium, Delhi-DPCC	36	Vivek Vihar, Delhi-DPCC
18 19	Mandir Marg, New Delhi-DPCC Mundaka, Delhi-DPCC	37	Wazirpur, Delhi-DPCC

2.3. Data Processing

The GIS Spatial Database and Spatial Analysis Software can help track air pollutants' effects. Air contamination maps may be used to calculate areas, which also help determine the sensitivity locations involving different pollutants. The number of people impacted can also be computed using air quality maps. Plans and decisions aided by air quality maps can positively impact lowering pollution levels. This paper evaluates air pollution through the Air Quality Index and maps over the study area. GIS provides a versatile toolkit to store and locate, convert and display real-world spatial data for different purposes [21]. A GIS cataloging and metadata management system could be used at every process stage to track data manipulation [22]. Those involve input data update, data simplification, interpolation methods, measurement methods, calculation parameters, and other considerations that can impact the precision of the results. Therefore, in the research on the future effects of air pollution, GIS is becoming more relevant. GIS allows the electronic representation of air quality impacts and is an essential method for the outcomes study. Integrating GIS with air pollution prediction models generates a quick and accurate environmental impact assessment of air pollution. GIS Database Management System makes storing, collecting, controlling, and managing noise data easier. Air pollution maps can be produced based on the interpolation techniques available in GIS. A continuous spatial model of pollution levels can be created within GIS. The GIS provides a convenient environment for publishing pollution maps on the internet. The air pollution map can be integrated with other thematic maps depending on their use.

2.4. Data Pre-Processing and Cross-Validation

The objective evaluation procedures were carried out using cross-validation techniques to analyze the different interpolation methods' precision, applicability, and efficacy. Cross-validation is the traditional technique for testing the precision of the effects of interpolation. Cross-validation is done by extracting information from the location, usually by one measurement at a time, measuring the value with the remaining evidence at that location, and then calculating the discrepancy between the true and the approximate value for each location [23]. The cross-validation method has been done by choosing five stations out of 37 stations in Delhi. We evaluated the difference between the actual data and the expected data of each interpolated process by measuring the mean error (ME) Equation (1) and the Root Mean Squared Error (RMSE) Equation (2) by various interpolation techniques. The ME tests the estimation, and the unbiased interpolation target should be near 0 [24,25]. The

RMSE is a test of the accuracy of the different prediction methods. It is as low for unbiased and reliable forecasts as possible. The ME and RMSE were determined using the following equations [24–30].

$$\mathrm{ME} = \frac{1}{\mathrm{n}} \sum_{\mathrm{i}=1}^{\mathrm{n}} [\mathrm{Z}(P_i) - \mathrm{z}(a_i)] \tag{1}$$

$$\mathrm{RMSE} = \sqrt{\frac{1}{\mathrm{n}} \sum_{\mathrm{i}=1}^{\mathrm{n}} [\mathrm{Z}(P_i) - \mathrm{z}(a_i)]^2} \tag{2}$$

where $\mathrm{Z}(P_i)$ is the prediction value, and $\mathrm{z}(a_i)$ is the actual value of validating point i, n = the number of validation points, ME = mean prediction error, RMSE = root mean square error, i = validating point, a_i = the position of validating point "i".

2.5. Data Estimation–Air Quality Index

Implementing ambient air quality standards is necessary to enhance a system to effectively regulate ambient air quality and avoid the adverse effects of air pollution [31–33]. Air Quality Index (AQI) may be calculated using pollutant concentration data and linear interpolation, as shown below [34,35]. Table 2 displays the breakpoints (BP) relating to each air quality parameter. The results corresponding to each CAQM station were then mapped using the Inverse Distance Weight technique in the ArcGIS environment and were further classified into different levels of AQI [36].

Table 2. Breakpoints (BP) for the AQI parameters.

Breakpoints (BP)		**Air Quality Index (AQI)**	**Category**
$PM_{2.5}$ (μg/m^3)	**PM_{10} (μg/m^3)**		
0.0–15.4	0–54	0–50	Good
15.5–40.4	55–154	51–100	Moderate
40.5–65.4	155–254	101–150	Unhealthy for sensitive groups
65.5–150.4	255–354	151–200	Unhealthy
150.5–250.4	355–424	201–300	Very unhealthy
>250.5	>425	301–400	Hazardous

3. Results and Discussion

3.1. Cross-Validation-Error Estimation

Equations (1) and (2) measured each interpolation layer's ME and the RMSE. Four interpolation methods (IDW, Kriging, NN, Spline) statistical parameters were calculated using ArcGIS and provided in Table 3.

Table 3. Statistical overview of the air pollution model interpolation errors (with measured sample values minus interpolated (μg /m^3)).

	IDW	**Kriging**	**NN**	**Spline**
MIN	37.11	51.92	37.58	−17.20
MAX	82.37	71.66	82.21	120.80
RANGE	45.26	19.74	44.63	138.01
MEAN	62.57	60.67	62.04	60.30
STD	6.95	4.76	7.88	21.40
ME	2.18	2.25	3.63	9.85
RMSE	5.62	6.05	5.70	24.40
GOODNESS RANK OF ME	I	II	III	IV
GOODNESS RANK OF RMSE	I	III	II	IV

The goodness rating is reserved separately for ME and RMSE. The mathematical parameter suggests the lowest error in the ME of IDW with 2.18. This indicates that IDW is less partial than the other interpolators [37]. Although IDW displayed a lower RMSE when comparing RMSE values, specific IDW is better than other interpolators. IDW shows a low ME since uncertain position estimation is based on spatial autocorrelation, and the rate of air quality in known areas is anisotropic. IDW demonstrates lower RMSE than other interpolation strategies, as the reference points are still in the same place in IDW modeling as the nodes or edges. This means that IDW preserves all the consistency of the input data when also modeling the values between known points [38]. IDW techniques were therefore used in this paper.

3.2. Data Interpolation and Mapping-Particulate Matter Concentration

The concentrations of air pollutants obtained at the CAQM stations (Table 1) have been measured, and their spatial distribution is mapped out. Figure 5 shows the distribution of $PM_{2.5}$, and Figure 6 indicates the concentration of Particulate Matter 10 (PM10).

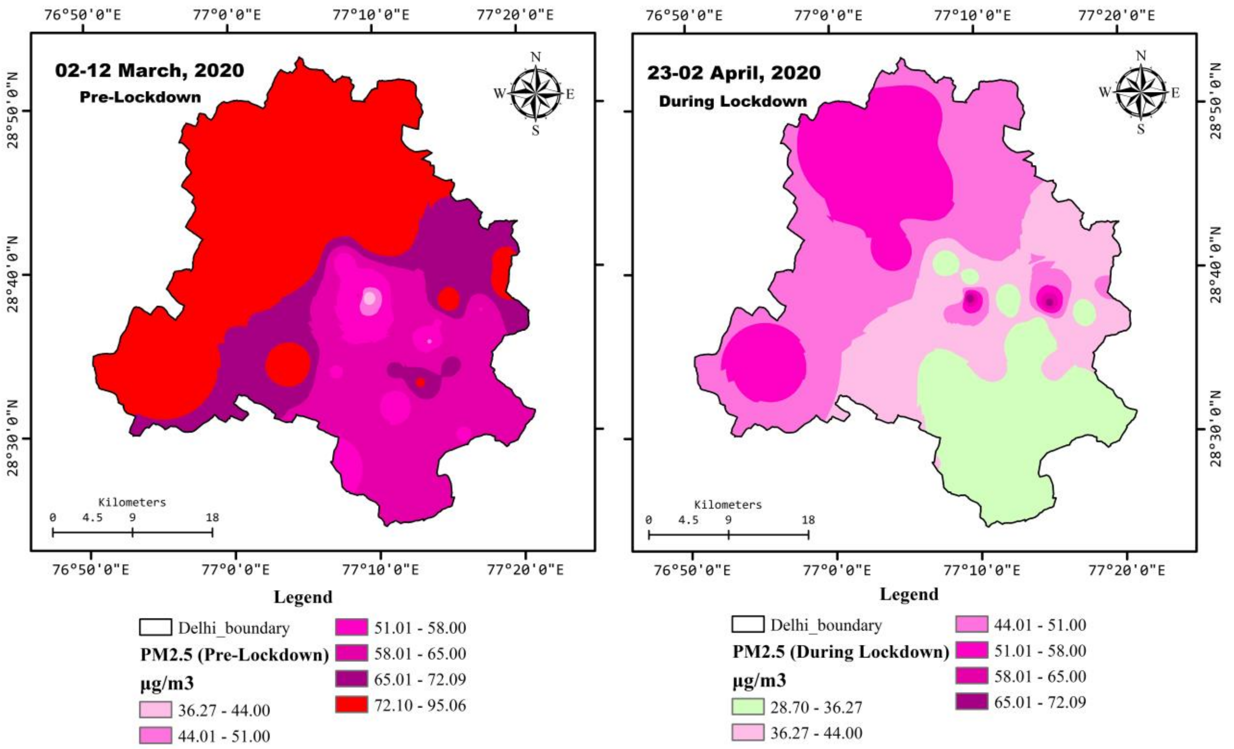

Figure 5. Distribution of $PM_{2.5}$ concentrations before and during the lockdown. The same classes have been provided with the same colour scheme for easy visualization of assessing the changes in the $PM_{2.5}$ before and during the lockdown. It must be noted that pre-lockdown period $PM_{2.5}$ ranges from 36.27 to 95.06 µg/m^3. In contrast, during the lockdown, it went down and ranged from 28.70 to 72.09 µg/m^3.

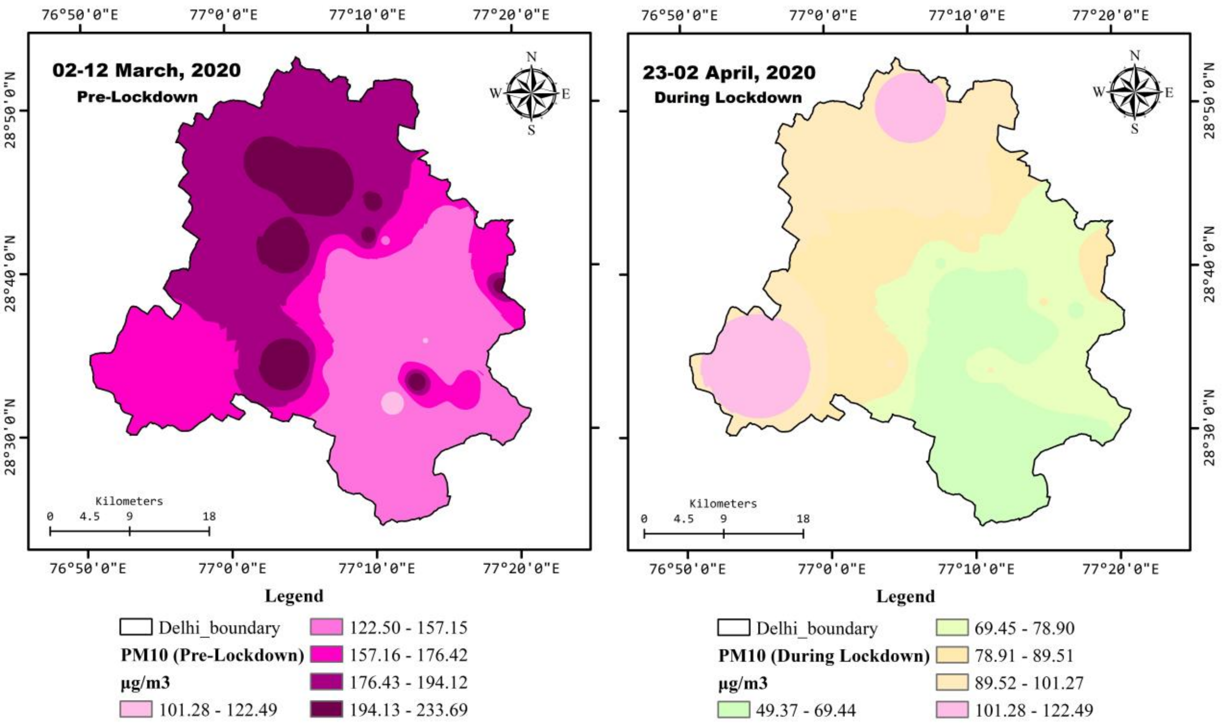

Figure 6. Distribution of PM_{10} pollutants before (12–22 March 2020) and during the lockdown (23 March–2 April 2020). It must be noted that only one class overlapped between the two periods of analysis, i.e., 101.28–122.49. This class has been provided the same color scheme in pre-lockdown period and during lockdown period maps. It must be noted that pre-lockdown period PM10 ranged from 101.28 to 233.69 μg/m^3. In contrast, during lockdown, it went down and ranged from 49.37 to 122.49 μg/m^3.

The levels of the concentrations are differentiated using color palettes (green is low concentration, and red is high concentration). In the distribution of $PM_{2.5}$ pollutants map, it is found that before the lockdown period, the maximum level of the concentrations of $PM_{2.5}$ was 95.06 μg/m^3, and the minimum was 36.27 μg/m^3, and during the lockdown, it reduced to the maximum value of 72.09 μg/m^3 and minimum value of 28.70 μg/m^3. It is also found that the North and North-West district of the Delhi region has the maximum concentration just before the lockdown period. Subsequent high concentrations were recorded in Delhi's West and Southwest districts, and the places near the South and New Delhi districts have recorded low concentrations. During the lockdown period due to SARS-CoV-2, the concentration of $PM_{2.5}$ was reduced in all districts.

The same trend was observed in the case of PM10. Before the lockdown period, the concentration of PM10 had a maximum value of 233.69 μg/m^3 and a minimum value of 101.28 μg/m^3. During the lockdown, it showed the same trend as $PM_{2.5}$ and reduced in all Delhi districts. The concentration of PM10 level reduced to almost half of what it was before the lockdown period. Figures 5 and 6 clearly show the change in the concentration level of $PM_{2.5}$ and PM10, respectively.

3.3. Data Interpolation and Mapping-Air Quality Index

The Air Quality Index (AQI) was estimated and displayed on the map for the measured PM $_{2.5}$ concentrations (Figure 7). In the AQI map, it is found that the AQI was classified into two groups before the lockdown period. One is an unhealthy level, and the other is unhealthy for sensitive groups of people. However, during the lockdown period, due to SARS-CoV-2 it changed, and the AQI levels fell into unhealthy for sensitive groups of people and moderate, respectively.

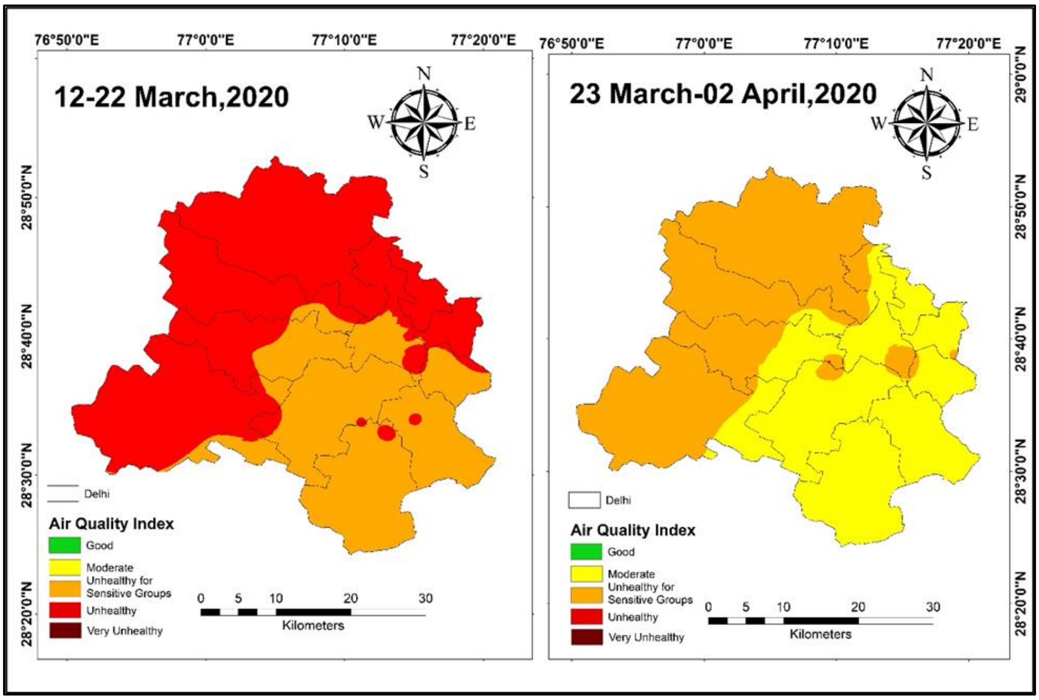

Figure 7. AQI map of $PM_{2.5}$ before (12–22 March 2020) and during the lockdown (23 March–2 April 2020).

The district, namely Northwest, North, and Southwest, changed from unhealthy to unhealthy for sensitive groups due to the SARS-CoV-2 lockdown. The remaining districts changed from unhealthy for sensitive groups to moderate levels.

Figure 8 shows the values of AQI estimated for each CAQM station before and during the lockdown period. During the lockdown, the station IHBAS, Dilshad Garden, Delhi–CPCB, showed the maximum reduction in the AQI, i.e., from 156 to 60 (62%), and the station ITO, Delhi–CPCB, showed the minimum decrease, from 160 to 148 (8%). However, for the Pusa, Delhi–IMD, the AQI level increased from 102 to 155 (52%).

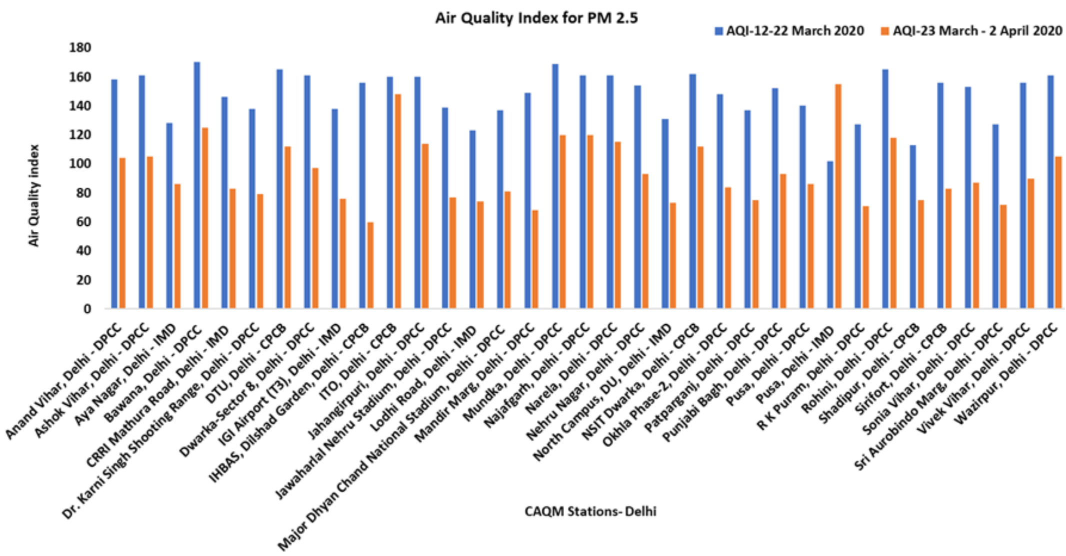

Figure 8. Comparison plot of AQI for $PM_{2.5}$ between the pre- and during-lockdown periods.

On comparing the districts-wise AQI for $PM_{2.5}$ (Table 4), it was found that the maximum reduction of mean AQI was in the case of Shahdara district, i.e., from 154 to 83 (46%).

The minimum reduction of mean AQI was found in the West district, i.e., from 147 to 102 (28%). Also, before the lockdown period, the mean AQI was highest in the North district (161) and lowest in the South and New Delhi districts (139). However, during the lockdown period, AQI reduced, and the same trend of maximum and minimum mean AQI levels is observed, i.e., highest for the North district (112) and lowest for the South (82), New Delhi (83), and Southeast (84) districts. Overall, the mean value of AQI for $PM_{2.5}$ showed a net reduction of 37%.

Table 4. District-wise comparison of AQI for $PM_{2.5}$.

S No.	District Name	12–22 March 2020			23 March–2 April 2020		
		Min	Max	Mean	Min	Max	Mean
1	North	151	170	161	95	125	112
2	North East	151	156	154	74	99	89
3	West	102	169	147	71	155	102
4	East	137	157	146	75	129	90
5	South West	138	162	154	87	120	108
6	Central	125	160	150	73	148	99
7	New Delhi	103	161	139	68	153	88
8	South	127	156	139	72	93	82
9	Shahdara	150	158	154	60	104	83
10	South East	123	154	144	74	93	84
11	North West	128	169	158	73	120	109

The air quality index (AQI) for the recorded PM10 concentrations was calculated and depicted on the map shown in Figure 9. The AQI map shows that the AQI falls into two categories before the lockdown period: one is unhealthy for sensitive groups, and the other moderate. During the lockdown period, however, most of the AQI levels changed to moderate levels and some to, good levels.

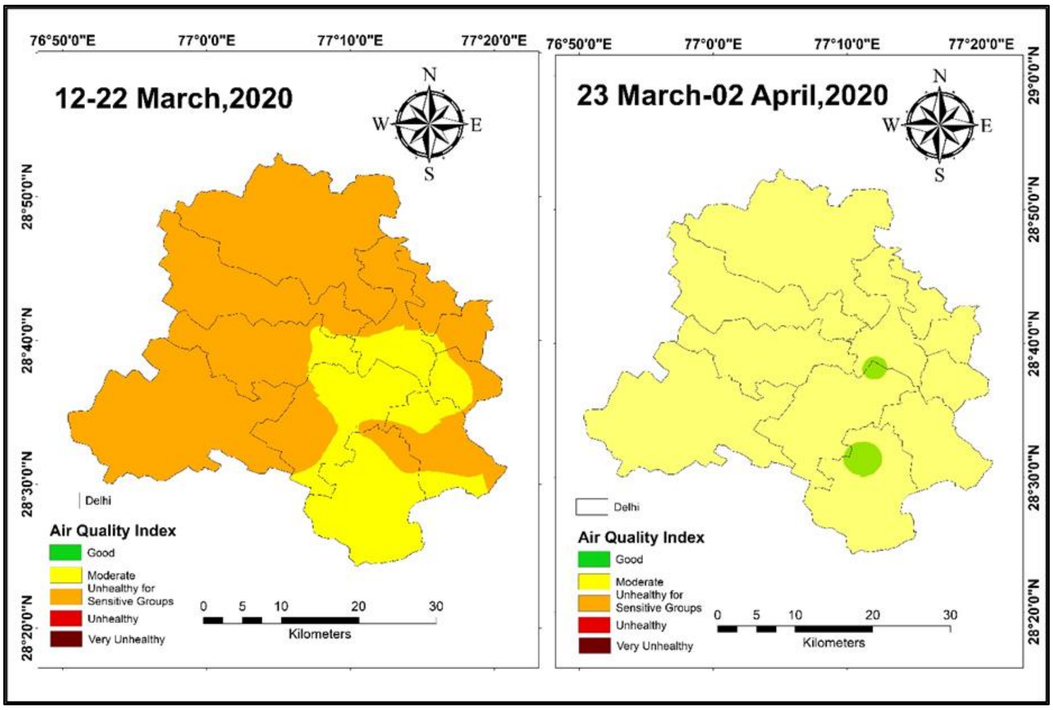

Figure 9. AQI map of PM_{10} before (12–22 March 2020) and during the lockdown (23 March–2 April 2020).

Figure 10 represents the AQI for PM 10 before and during the lockdown; it is evident from the graph that the AQI level was reduced by almost 50% in almost all of the stations. The Dwarka-Sector 8, Delhi PCC station, showed a maximum reduction from 145 to 66 (55%), and the station ITO, New Delhi–CPCB, showed a minimum reduction, i.e., from 88 to 62 (30%).

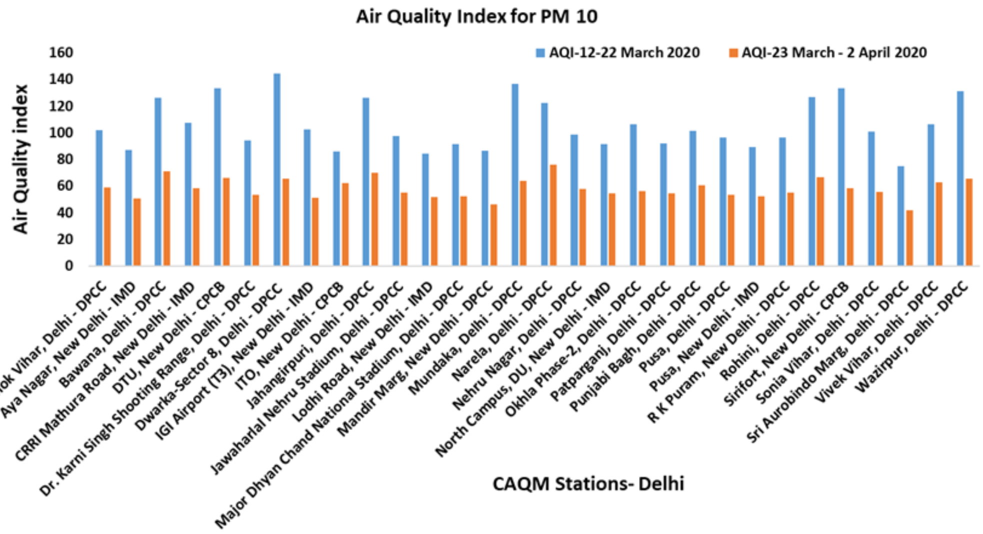

Figure 10. Comparison plot of AQI for PM10 between the pre- and during-lockdown periods.

On comparing the district-wise AQI for PM 10 (Table 5), it was found that the maximum reduction of mean AQI was in the case of the Northwest district, i.e., from 121 to 64 (47%). The minimum reduction of mean AQI was found in the West district, i.e., from 101 to 57 (43%). As well, before the lockdown period, the mean AQI was highest in the North district (122) and lowest in the South district (97). During the lockdown period, however, AQI reduced, and the same trend of maximum and minimum mean AQI levels is observed, i.e., the highest for the North district (68) and the lowest for the South district (53). Overall, the mean value of AQI for PM10 showed a net reduction of 46%.

Table 5. District-wise comparison of AQI for PM10.

S No.	District Name	12–22 March 2020			23rd March–02nd April 2020		
		Min	Max	Mean	Min	Max	Mean
1	North	102	134	122	59	76	68
2	North East	99	114	104	55	63	58
3	West	89	136	114	52	64	59
4	East	89	128	101	55	62	57
5	South West	101	144	113	54	65	59
6	Central	86	124	102	47	68	58
7	New Delhi	84	145	101	46	66	54
8	South	75	133	97	42	61	53
9	Shahdara	95	131	107	57	63	60
10	South East	84	121	101	52	58	56
11	North West	97	137	121	55	69	64

As a result of COVID-19, normal life on Earth has been disrupted in ways that have not been seen in the last one hundred years [39,40]. Workers and the impoverished are hit worst by COVID-19′s restrictions, which have led to the global shutdown of all commercial and industrial units [41]. While a reduction in air pollution is desirable, it is not acceptable if this comes at the expense of food insecurity [42]. Multiple large, populated cities in northern India appear to have seen significant improvements due to the lockdown [43–46].

Over the past two decades, the phenomena underpinning global warming, climate change, and pollution in the Earth's atmosphere have become central issues of scientific inquiry [47]. Air pollutants such as ozone (O3), nitrogen dioxide (NO2), carbon monoxide (CO), particulate matter (PM) in various size fractions (PM0.1 m, $PM_{2.5}$ m, and PM10 m), volatile organic compounds (VOCs), and polycyclic aromatic hydrocarbons (PAHs) have had a significant impact on ecology, environment, and human health [48–51]. Toxic nitrogen oxide (NOx) emissions in both developing (India, China, etc.) and western industrialized countries were drastically reduced due to COVID-19 limitations on diesel, gasoline, and other petroleum fuel combustion [47–49]. Multiple studies have been done to learn how long-term lockdowns affect local and worldwide air quality [52–63]. The air quality greatly improved, according to these studies, once factories and cars stopped running. Despite the lockdowns, environmental and human health are again negatively impacted by particulate matter and pollutant gases (NOx/SOx/CO) in the post-COVID era [64,65]. Aerosols have been found to affect the radiation budget, human health, and even the strength of monsoons in a number of studies [66,67]. Increasing cardiovascular mortality is a known effect of chronic exposure to particulate matter, NOx, and ozone [68,69]. Particulate matter ($PM_{2.5}$ and PM10) emissions are the greatest in India, followed by NO2, SO2 and CO, according to the national ambient air quality monitoring programme [70].

The study has demonstrated how, due to the lockdown, after years of poor air quality, certain Delhi neighborhoods were able to breathe easier. The findings also suggest that emergency lockdown tactics could be an option to deal with extreme air pollution if they are executed in a way that does not negatively impact the economy and poorer classes of society [71–76]. Based on this, there is a need to identify nature's cyclic healing rate against anthropogenic activities. The government should focus on formulating specific policies to curb air pollution in Delhi. Some short-term policies like intermittent banning of certain anthropogenic activities (construction, mining, and burning of farm waste) based upon cyclic AQI patterns, medium-term policies such as preventing open incinerations, smog tower installations, and long-term policies such as vehicle emission norms, industrial operational timings, and public awareness campaigns.

4. Conclusions

While the whole nation was terrified by the outbreak of the SARS-CoV-2 pandemic, nature, on the other hand, was healing temporarily. This paper helped to explore the linkage between the air quality and nationwide lockdown due to SARS-CoV-2 for the city of Delhi using GIS technology. Data from almost 37 CAQM stations were observed before and during the lockdown period. The city's Air Quality Index was reduced by nearly 37% and 46% concerning $PM_{2.5}$ and PM10, respectively, due to the lockdown. Air pollution reduction could be mainly due to the decline in economic activities, related emissions, and vehicular emissions. The methodology employed in GIS technology helped to monitor the Air Quality Index changes efficiently. Furthermore, geo-visualization using GIS proved a better method for monitoring air pollution. However, the weather parameters such as wind speed, temperature, and altitude, which affect pollution dispersion, must be studied for high precision. Finally, it is possible to conclude that when human activities are abruptly ceased, the natural pace of healing exceeds the caused disruptions, resulting in a lower AQI, proving that this pandemic has given a small window for the environment to breathe and helped the districts of Delhi to recover from serious air quality situations. Also, the results show that such lockdown strategies, if implemented so that the economy and lower segments of society are not affected, could be a possible emergency measure to combat severe air pollution.

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