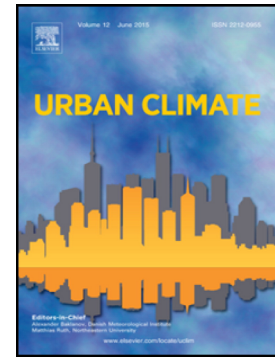


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Regional scenario of air pollution in lockdown due to COVID-19 pandemic: evidence from major urban agglomerations of India

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Abstract

Air pollution in India during COVID-19 lockdown, which imposed on 25th March to 31st May, 2020, has brought a significant improvement in air quality. The present paper mainly focuses on the scenario of air pollution level (PM_{2.5}, PM₁₀, SO₂, NO₂ and O₃) across 57 urban agglomerations (UAs) of India during lockdown. For analysis, India has been divided into six regions - Northern, Western, Central, Southern, Eastern and North-Eastern. Various spatial statistical modelling of composite air quality index (CAQI) have been utilised to examine the spatial pattern of air pollution level. The result shows that concentration of all air pollutants decreased significantly (except O₃) during lockdown. The maximum decrease is the concentration of NO₂ (40%) followed by PM_{2.5} (32%), PM₁₀ (24%) and SO₂ (18%). Among 57 UA's, only five - Panipat (1.00), Ghaziabad (0.76), Delhi (0.74), Gurugram (0.72) and Varanasi

(0.71) had least improvement in air pollution level considering entire lockdown period. The outcome of this study has an immense scope to understand the regional scenario of air pollution level and to implement effective strategies for environmental sustainability.

Keywords: Covid-19; lockdown; air quality; urban agglomerations; particulate matter; million plus cities.

1. Introduction

The air pollution in many countries of the world has come under serious threat on environmental sustainability and public health (Das et al., 2020). As per the report of WHO (2016), about 60% of the people living in urban areas are severely exposed to air pollution due to rapid urbanisation. Even 98% cities of the low-middle income countries and 56% cities of high income countries are not able to meet WHO's (2016) guidelines. More than 4.2 billion people died due to severe health disease caused by air pollution (WHO, 2016). But during lockdown due to outbreak of COVID-19 has brought a significant improvement in air quality across the world (Dantas et al., 2020; Das et al., 2021; Ibe et al., 2020; Otmani et al., 2020; Sharma et al., 2020; Sikarwar and Rani, 2020; Tobías et al., 2020; Xu et al., 2020). Like other countries of the world, India also under complete lockdown from 25th March, 2020 to 31st May, 2020).

Recently, many studies were performed across the cities of the worlds to examine the immediate impact of lockdown on air quality (Dantas et al., 2020; Das et al., 2021; Ibe et al., 2020; Otmani et al., 2020; Navinya et al., 2020; Sarkar et al., 2020; Sharma et al., 2020; Sikarwar and Rani, 2020; Singh and Chauhan, 2020; Tobías et al., 2020; Xu et al., 2020). In China, the concentration of major air pollutants (such as PM_{2.5}, PM₁₀, SO₂, CO and NO₂) in three major cities declined by

30.1%, 40.5%, 33.4%, 27.7% and 14.9%, respectively during lockdown (Xu et al., 2020).

Several studies also recorded the similar results for major cities of Spain, Brazil, China, Morocco (Dantas et al., 2020; Otmani et al., 2020; Tobías et al., 2020; Xu et al., 2020). In India, a number of studies performed to assess the impact of lockdown on air quality (Jain and Sharma, 2020; Mahato et al., 2020; Mahato and Ghosh, 2020; Singh and Chauhan, 2020; Sharma et al., 2020).

After a quick review of the previously published studies on the assessment of air quality, the notable research gaps are: studies were mainly focussed on megacities such as Delhi (Mahato et al., 2020; Sikarwar and Rani, 2020), Kolkata (Sarkar et al., 2020) and most polluted cities of India rather than other cities across the country (Mahato and Ghosh, 2020) or state (Sharma et al., 2020), few studies were concentrated towards examining impact of lockdown across regional level (Navinya et al., 2020) and (a) no studies have been performed to assess the impact of lockdown considering million plus cities (population more than 1 million) and large UAs of India, To address these present research gaps, the present study tried to investigate the impact of lockdown on air quality across the 57 UAs of India, The outcome of the study will help to understand the regional scenario of air pollution and effective strategies to be implemented at regional level across the cities of India.

As per as census of India (2011), about 31% of the total population of 12.1 billion lives in urban areas. The Census report stated that there were 468 UAs/ towns with a population of minimum 100,000. More than 70% of the total urban population lives in UAs/ towns. Out of 468, 53 UAs/towns were million plus cities and 42% urban population lives here. In addition to this, among UAs/ cities, there were three large UAs with population more than 10 million (known as megacities) and they are Greater Mumbai (18.4 million), Delhi (16.3 millions) and Kolkata (14.1 millions). But unfortunately these megacities are most polluted. As per the World Air Quality Report (2018), Delhi notified as most polluted capital city of the world (annual average $PM_{2.5}$

(113.5 $\mu\text{g}/\text{m}^3$). In addition, from the same report it can be extracted that (a) out of 15 most polluted cities of South Asia, 13 cities were located in India (b) Gugugram UA (In Northern India) was the most polluted city of India (annual average $\text{PM}_{2.5}$ -135.8 $\mu\text{g}/\text{m}^3$) followed by Ghaziabad UA (135.2 $\mu\text{g}/\text{m}^3$), Faridabad UA (129.1 $\mu\text{g}/\text{m}^3$), Bhiwadi UA (125.4 $\mu\text{g}/\text{m}^3$), Noida UA (123.6 $\mu\text{g}/\text{m}^3$) and Patna UA (119.7 $\mu\text{g}/\text{m}^3$). But due to lockdown of entire country, significant improvement of air quality was reported from these major cities of India. Therefore, to assess regional scenario of air pollution level, two basic research questions have been formulated- (a) was there any impact of lockdown on air pollution across the major UAs in India? (b) Is there any spatial variation of air pollution level at regional scale? To address these two research questions, air pollution across the 57 UAs of India has been assessed.

2. Materials and Methods

2.1. About study area

In this present study 57 UAs (with population of 1 lakh and above) have been selected from different regions of the country (Table 1 and Figure 1). Out of 57 UAs, there are 31 million plus cities (census of India, 2011). Million plus cities are those cities those have population more than 1 million. Mumbai is the largest UA (population 18.4 million) followed by Delhi (16.3 million), Kolkata (14.0 million), Chennai (8.65 million), and Bangalore (8.52 million)

Figure 1 Study maps showing distribution of selected UAs of India

2.2. Distribution of UAs

As per census of India (2011), there were 474 UAs in India. But in the present study, 57 major UAs have been considered and 31 of them are under million plus cities. As shown in Table 1, the UAs were categorized into six regions namely- Northern (18), Central (14), Southern (11),

Western (7), Eastern (6) and North-Eastern (1). More than 30% of total UAs were selected from Northern India followed by Central (24%) and Western (17%) since most of the polluted cities are lies in these three regions and they are: Delhi, Gurggram, Kanpur, Lucknow, Agra, Varanasi, Muzaffarnagar, Hisar and Jaipur (Table 1) (Gargava and Rajgopalan, 2016; Pant et al., 2016; Srimuruganandam and Nagendra, 2012; Lui et al., 2013; Villalobos et al., 2015).

2.3. Data used

In this study, data regarding concentration of air pollutants ($PM_{2.5}$, PM_{10} , O_3 , CO , SO_2 and NO_2) over major UAs were collected from urban emission info online portal (<http://urbanemissions.info/blog-pieces/india-airquality-covid-19/>). This online portal provides air quality data of India during COVID-19 in different phases of lockdown: phase I (24 March to 14 April, 2020), phase II (15 April to 3 May) and phase III (4 May to 17 May) and phase IV (18 May to 31 May). All the air quality data for each UAs were assessed from official monitoring network maintained and operated by Central Pollution Control Board (CPCB). The CPCB portal provides air quality data of 120 cities of India prior to 30 days of lockdown and during different phases of lockdown.

3.1. Methodology

3.1.1. Spatial statistical modelling

Spatial statistical modelling has been used to examine the spatial concentration of air pollutants across the 57 UAs of India. These multidisciplinary statistical techniques include (a) Getis–Ord G^* statistics was used to assess cluster analysis which easily identifies the statistically significant spatial clusters (Getis and Ord, 1992; Ord and Getis, 1995; Osei et al., 2008) and used to examine spatial concentration of air pollutants (Ye et al., 2018; Zhang et al., 2018; Xia et al., 2017, Dong et al., 2014), (b) local indicators of spatial autocorrelation (LISA)- one of the fundamental entities of any spaces (Xia et al., 2017). In this present study, these two widely used

techniques were used to examine spatial concentration of air pollutant across UAs in India.

These are explained below:

(a) Getis-Ord*- Statistics

Z value of Getis-Ord G* statistics helps to identify the differences between cold spot and hot spot with different confidence level of 99%, 95% and 90%, respectively by following formula

(Ord and Getis, 1995):

$$Gi^* = \frac{\sum_{j=1}^n w_{i,j} w_j - \bar{x} \sum_{j=1}^n w_{i,j}}{\sqrt{\frac{\sum_{j=1}^n w_{i,j}^2 - (\sum_{j=1}^n w_{i,j})^2}{n-1}}} \quad (1)$$

Where w_j is the weight of i th sub-component, w_{ij} is the spatial weight between i and j th components, with n number of features and x_j is the value of j th component with \bar{x} as mean and s as standard deviation.

$$\bar{x} = \frac{\sum_{j=1}^n x_j}{n} \quad (2)$$

$$s = \sqrt{\frac{\sum_{j=1}^n x_j^2}{n} - (\bar{x})^2} \quad (3)$$

(b) Cluster analysis

Local Moran's I Index (Anselin, 1996) was used for clustering analysis.

$$I_i = \frac{(x_i - \bar{x})}{S_{i2}} \sum_{j=1, j \neq i}^n w_{ij} (x_j - \bar{x}) \quad (4)$$

$$S_{i2} = \frac{\sum_{j=1, j \neq i}^n (x_j - \bar{x})^2}{n-1} \quad (5)$$

Where, n is the total number of selected UAs of the study area, x_i and x_j represents the air pollutant ion level of i th and j th UAs; \bar{x} is the mean value of the air pollutants and w_{ij} is the spatial weight of the UA j and i , respectively.

3.1.2. Normalization of Data

Before construction of composite score for each air pollutants across UAs, the entire data were standardized to make them unit free using range equalization methods (Das et al., 2019; 2020) (called normalization of data). The standardized value of data ranges from 0 to 1 where 0 indicates relatively very good air quality and the value close to 1 indicates relatively very poor air quality.

All the air pollutants data have been normalized using following equation:

$$X_{ic} = \frac{X_{ij} - X_{ij \min}}{X_{ij \max} - X_{ij \min}} \quad (6)$$

Where, X_{ic} =Scale equivalence, X_{ij} =Observed concentration of a particular air pollutant; $X_{ij \max}$ = highest concentration of that air pollutant and $X_{ij \min}$ = lowest concentration of that air pollutant within entire dataset respectively.

3.1.3. Construction of a Composite Air Quality Index (CAQI)

In this study, a composite air quality index (CAQI) was developed to examine the regional variation of air quality level across UAs of India. It has a great advantage because of its comprehensiveness, composite as well as multidimensionality. The score of the air pollutants have been calculated in different phases of lockdown with the help of following formula:

Step: I Computation of composite score for a particular lockdown phase-

$$CS_{api} = \frac{\sum A_{p1} + \sum A_{p2} + \dots + \sum X_{pi}}{\sum A_{pn}} \quad (7)$$

Where, CS_{api} refers to the composite score of air pollutants during a particular lockdown phase; $\sum A_{p1}$ and $\sum A_{p2}$ refers to the concentration of air pollutants (such as $PM_{2.5}$, PM_{10} etc.) and lastly $\sum A_{pn}$ refers to the number of air pollutants respectively.

Step: II Computation of final score during entire phase of lockdown

$$CS_p = \frac{\sum P_i + \sum P_{ii} + \sum P_{iii} + \sum P_{iv}}{\sum P_n} \quad (8)$$

Where, Composite Score during entire periods of lockdown; $\sum P$ refers to the phases of lockdown (here from phase I and phase IV) and $\sum P_n$ refers to the total number of lockdown phases (four in this study).

3.1.4. Statistical Analysis

In the present study, a number of statistical tools were used to examine the regional scenario of air pollution level over UAs in India. These statistical tools were Co-efficient of variation (C_v), Analysis of variance (ANOVA) and Correlation Analysis (r). First, C_v was applied to examine the relative difference of air pollution level in different phases of lockdown over UAs and previously used to assess the degree of dispersion on air pollutants (Jin et al., 2017; Song et al., 2017; Xu et al., 2017; Ibe et al., 2020). The higher value of C_v indicates greater degree of dispersion of air pollution and vice versa (Heetal., 2017). Second, ANOVA was used to understand the difference of air pollution level over the UAs in different phases of lockdown and previously used to examine the concentration of $PM_{2.5}$ (Chen et al., 2019; Ibe et al., 2020). Third, Correlation Analysis (r) was used to assess the direction of linear relationship among air pollutants (Ibe et al., 2020).

4. Result and Discussion

4.1. Spatio-temporal variation of air pollutants over UAs

In the present study, the concentration of major air pollutants was assessed at regional scale. As listed in Table 1, the entire country is divided into six major regions for better understanding the spatial heterogeneity of air pollutants distribution. The result shows that most of cities located in Northern, Central and Western India are highly polluted. The detail descriptions of the regions are given below:

4.1.1. Northern India

For the present study, 18 UAs considered from this region which covers almost 30% of the total UAs under study. The major UAs of this region are Delhi, Gurugram, Jaipur, Udaipur, Amritsar, and Jalandhar. The details of air pollution level before and during the lockdown are mentioned below:

The average of 30 days of prior to lockdown of $PM_{2.5}$ ($\mu g/m^3$) was 50.7 $\mu g/m^3$ which declined to 45.1 by the end of phase IV of lockdown. During the entire periods of lockdown, highest $PM_{2.5}$ was reported in Delhi (60.9) followed by Yamuna Nagar (60.8) and Palwal (58). The phase wise average concentration of $PM_{2.5}$ across the UAs was 29.3 (phase I), 36.9 (phase II), 40.9 (phase III) and 45.1 (phase IV), respectively. The average value of $PM_{2.5}$ during the IV phases of lockdown is increasing due to withdrawal of some restrictions (movement of private vehicle etc.) by the local authority after end of phase III. **Figure 2** shows the concentration of $PM_{2.5}$ across all the UAs considered for the present study.

Figure 2 Concentration of $PM_{2.5}$ across the UAs

The average of 30 days of prior to lockdown of PM_{10} ($\mu g/m^3$) was 104.9 across the UAs which declined to 98.3 during lockdown period. The highest concentration of average of 30 days prior to lockdown was recorded in Panipat (180) followed by Delhi (158) and Sonipath (144). During the entire periods of lockdown, the average concentration of the same locations reduced to 178, 125 and 139, respectively. The phase wise average concentrations of PM_{10} across the

UAs were: phase I (63.9), phase II (88.7), phase III (95.8) and phase IV (127.2) (**Figure 3**).

During phase IV, the average value of PM_{10} increased due to withdrawal of some restrictions by the local authority.

Figure 3 Concentration of PM_{10} across the UAs

There were no significant changes in average of SO_2 ($\mu\text{g}/\text{m}^3$) before and during lockdown. The result shows that the average of 30 days of prior to lockdown of SO_2 ($\mu\text{g}/\text{m}^3$) across UAs in this region was 16.4 and reached to 16.8 during the lockdown periods. Before lockdown, the highest value was recorded in Karnal (38.3) followed by Sonipat (28.1), Panipat UA (17.8) Jaipur (14.9) and Delhi (14.6). On the other hand, during the entire period of lockdown, highest SO_2 was recorded in Jodhpur (50.5) followed by Panipat (44.5) and Karnal (46.9) during phase IV (**Figure 4**). From the record it was observed that the concentration of SO_2 is the highest in phase IV, since local authority/state government has withdrawal some of the restrictions by the end of phase III and allowed to ply private vehicles.

Figure 4 Concentration of SO_2 across the UAs

It is interesting to see from the result that the average concentration of O_3 ($\mu\text{g}/\text{m}^3$) increased by 28% during lockdown in comparison to 30 days' average prior to lockdown. It is due to the fact that O_3 is formed by the photochemical reactions of oxides of nitrogen (NO_x), volatile organic compounds influenced by gases available in air and in presence of sunlight and heat and so it is not formed due to direct emission. During lockdown, ozone thus formed escapes to cleaner areas and reduced NO_2 couldn't restrict it. The phase wise average concentration of O_3 across the UAs were: phase I (44.8), phase II (51.8), phase III (63.6) and phase IV (54.6) where as average concentration 30 days' average prior to lockdown was 42.5 (**Figure 5**).

Figure 5 Concentration of O_3 across the UAs

The average concentration of NO_2 ($\mu\text{g}/\text{m}^3$) across UAs of Northern India was decreased by 34% during lockdown in comparison to 30 days' average prior to lockdown. The result shows that before lockdown the highest concentration was in Sonipat (77) followed by Delhi (39.8) and Yamunagar (39.4). By the end of phase IV, the value of NO_2 of the same locations reached to 52.2, 30.8 and 33.1, respectively (**Figure 6**).

Figure 6 Concentration of NO_2 across the UAs

4.1.2. Central India

In this region, four states are included: Madhya Pradesh, Uttar Pradesh, Chhatisgarh and Uttarakhand. From these four states, 14 UAs were considered which covers almost 24% of the total UAs. The details of air pollution level before and during the lockdown are mentioned below:

The average of 30 days of prior to lockdown of $\text{PM}_{2.5}$ ($\mu\text{g}/\text{m}^3$) of all UAs of this region was 54.7 which declined to 40.5, 43.5, 40.4 and 47.4 during phases I-IV, respectively. Prior to lockdown, the average of 30 days was recorded in Ghaziabad (86) followed by Lucknow (69), Muzaffarpur (68) and Varanasi (62.6) whereas during entire period of lockdown, highest concentration of $\text{PM}_{2.5}$ was recorded in Raeban (80) followed by Muzaffarpur (70) and Ghaziabad (62).

The result shows that the average of 30 days of prior to lockdown of PM_{10} ($\mu\text{g}/\text{m}^3$) was 84.3 across the UAs which declined to 83.0, 80.3 and 84.2 during phase I-III, respectively but increased to 132.6 during phase IV of lockdown. The increase in value is due to withdrawal of some restrictions by the local authority during phase IV like allowing the private vehicles to ply, reducing the period of night curfew etc.

From the result it observed that average of 30 days of prior to lockdown of SO_2 ($\mu\text{g}/\text{m}^3$) across UAs in this region was 16.7 and reached to 15.0 considering entire period of lockdown.

30 days prior to lockdown, the highest value was recorded in Ratlem (66.8) followed by Agra (27.2), Varanasi (23.8 $\mu\text{g}/\text{m}^3$) and Gwalior (20.1) where as during lockdown, the highest concentration was recorded in Varanasi (40.87) followed by Agra (29.38), Gwalior (21.12) and Ghaziabad (19.8).

Like Northern regions in Central India too, O_3 was the only air pollutants that increased during lockdown periods and its justification has been given under section 4.1.1. The average concentration of O_3 ($\mu\text{g}/\text{m}^3$) prior to 30 days of lockdown was 38.5 which increased to 39.6, 43.2, 54.7 and 54.2 during phase I-IV of lockdown, respectively.

The average of 30 days prior to lockdown of NO_2 ($\mu\text{g}/\text{m}^3$) concentration across UAs of this region was 37.7 which reduced to 22.0 by the end of lockdown period. The highest percentage decrease in NO_2 by the end of lockdown to 30 days prior was observed in Bhopal (64) followed by Ratlem (62.96) and Indore (50.65).

4.1.3. Southern India

In this study, 11 UAs were selected comprising 19% of total UAs of India. The major UAs of Southern India are Chennai, Coimbatore, Hyderabad, Tirubantapuram, Kochi, Kozikode.

The average of 30 days prior to lockdown of $\text{PM}_{2.5}$ ($\mu\text{g}/\text{m}^3$) across the UAs of this region was 34.6 which declined to 26.9, 23.1, 20.2 and 20.9 during phases I-IV, respectively. Prior to lockdown, the average of 30 days was recorded in Kannur (48.4) followed by Kollam (45.6), Kochi (43.1) and Coimbatore (38.2) where as during entire period of lockdown, the average was highest in Kannur (30.85) followed by Hyderabad (30.58), Kozikode (24.50) and Coimbatore (23.93).

The result shows that the average of 30 days of prior to lockdown of PM_{10} ($\mu\text{g}/\text{m}^3$) was 64.3 across the UAs which declined to 51.9, 39.3, 42.8 and 50.3 during phase I-IV, respectively. During 30 days prior to lockdown, the average concentration of PM_{10} was highest in Kochi

(121.9) followed by Kannur (83.9), Kozhikode (65.1) and Tirubantapuram (60.2). In comparison to average concentration of 30 days prior to lockdown to entire period of lockdown, the maximum percentage decrease in PM_{10} is observed in Kochi (69%).

Out of all the regions, this region has the lowest value of SO_2 ($\mu g/m^3$) of all UAs. From the result it was observed that average of 30 days of prior to lockdown of SO_2 ($\mu g/m^3$) was 8.1 and reached to 6.0 by the end of phase IV of lockdown. 30 days prior to lockdown, the highest value was recorded in Kochi (20.2) followed by Chennai (10.8), Kollam (9.1) and Coimbatore (9) where as during lockdown, the highest concentration was recorded in Kochi (20) followed by Tirupati (10) and Chennai (8.8).

Unlike other regions, in Southern India, the concentration of O_3 decreased during lockdown period. The average concentration of O_3 ($\mu g/m^3$) prior to 30 days of lockdown was 38.7 which reduced to 27.0 by the end of lockdown. O_3 is formed by the photochemical reactions of oxides of nitrogen (NO_x) and influenced by the sunlight and heat. Therefore, in the lockdown periods, the decrease value of O_3 signifies that sunlight and heat was subtropical and most of the area is exposed to sea and due to which O_3 could not be formed properly and presence of reduced NO_x couldn't be helped to escape to cleaner areas.

The average of 30 days prior to lockdown of NO_2 ($\mu g/m^3$) concentration across UAs of this region was 21.5 which reduced to 16.1, 15.4, 15.2, 19.1 during phase I-IV of lockdown, respectively. The highest concentration of NO_2 prior to average of 30 days of lockdown was observed in Coimbatore (41.8), Mysore (30.3) and Tirupati (25.2) in descending order whereas during the entire lockdown period, the average concentration was highest in Coimbatore (44.82) and followed by Hyderabad (22.77) and Chennai (18.6).

4.1.4. Western India

In Western India, from 3 states (Maharashtra, Gujarat and Goa) total 9 UAs were selected (9% of total UAs of India). The major UAs in this region are: Mumbai (largest UA of India), Nashik, Pune, Ahmedabad and Ankeshwar. The details of air pollutants are as below:

The result shows that before lockdown average concentration of $PM_{2.5}$ ($\mu\text{g}/\text{m}^3$) across the UAs of Western region of India was 55.0 that reached to 29.1 (47.1% decrease) by the end of lockdown. Before lockdown, highest concentration of $PM_{2.5}$ was Bhiwandi (98.8) followed by Ankeshwar (61.9), Ahmedabad (60) and Pune (54.8) whereas during the entire period of lockdown the above value decreased to 79.2, 43.6, 33.33 and 31.2, respectively.

The result shows that the average of 30 days of prior to lockdown of PM_{10} ($\mu\text{g}/\text{m}^3$) was 102.6 across the UAs which declined to 60.5, 62.5, 65.0 and 65.4 during phase I-IV, respectively. During 30 days prior to lockdown, the average concentration of PM_{10} was highest in Mumbai (135) followed by Ankeshwar (132.5), Ahmedabad (128.5) and Bhiwandi UA (102) whereas considering entire period of lockdown, the average concentration was highest in Bhiwandi (107) followed by Ankeshwar (8.4), Ahmedabad (78.95) and Mumbai (69.05).

From the result it was observed that average of 30 days of prior to lockdown of SO_2 ($\mu\text{g}/\text{m}^3$) was 36.1 and reached to 13.1 with reduction of 63.7% by the end of lockdown. 30 days prior to lockdown, the highest value was recorded in Ahmedabad (57.7) followed by Aurangabad (55.7), Pune (48.4) and Bhiwandi (47.8) whereas by the end of lockdown, these values decreased to 27.3, 33.2, 29.3 and 34.2, respectively.

The average concentration of O_3 ($\mu\text{g}/\text{m}^3$) prior to 30 days of lockdown was 54.7 which was increased to 57.8 and 55.9 during phase I and phase III of lockdown, respectively whereas the average value decreases to 53.6 and 51.0 during phase II and phase IV, respectively. If the

average value of entire lockdown period is considered, the value of O_3 is almost similar to the average value of 30 days prior to lockdown.

The average of 30 days prior to lockdown of NO_2 ($\mu g/m^3$) concentration across UAs of this region was 36.1 which reduced to 19.7, 13.7, 16.2, 19.7 during phase I-IV of lockdown, respectively. The highest concentration of NO_2 prior to average of 30 days of lockdown was observed in Bhiwandi (64.8), Nagpur (53.21), Ahmedabad (48.1) and Mumbai (37.5) in descending order where as considering entire lockdown period, the values reduced to 51.2, 36.2, 28.9 and 22.7, respectively.

4.1.5. Eastern India

There are 6 major UAs (10% of total UAs of India) in Eastern India which belongs to 5 states (Table 1) and they are: Kolkata, Asansol, Siliguri, Patna, Gaya and Muzaffarpur. Among all UAs of India, Gaya, Patna and Muzaffarpur are the most polluted UAs (WHO 2018). The details of air pollutants are as below:

The result shows that before lockdown average concentration of $PM_{2.5}$ ($\mu g/m^3$) across the UAs of Western region of India was 58.5 that reached to 23.6 (reduction of 65.5%) by the end of lockdown. Before lockdown, highest concentration of $PM_{2.5}$ was in Siliguri (52.8) followed by Muzaffarpur (21.4) and Asansol (19.5) whereas by the end of lockdown these values decreased to 57.45, 18.75, and 9, respectively.

The result shows that the average of 30 days of prior to lockdown of PM_{10} ($\mu g/m^3$) was 97.0 of all UAs of this region which declined to 69.7 (reduction of 28.1%) by the end of phase IV. During 30 days prior to lockdown, the average concentration of PM_{10} was highest in Gaya (77.2) followed by Kolkata (83.9) and Muzaffarpur (67.0) which decreased to 75.8, 67.5 and 46.3, respectively during lockdown period.

The concentration of SO₂ across UAs of Eastern India decreased by 29.6% by the end of lockdown in comparison to average of 30 days prior to lockdown. The maximum decline was recorded in Asansol (53%) followed by Patna (18 %) and Muzaffarpur (12%).

The average concentration of O₃ (µg/m³) prior to 30 days of lockdown was 55.1 which increased to 62.9 during phase I. By the end of phase II-IV the value decreased to 39.3, 52.0 and 42.8. As mentioned in section 4.1.1, O₃ is formed during photochemical reactions of oxides of nitrogen (NO₂), volatile organic compounds influenced by gases available in air and in presence of sunlight and heat and so it is not formed due to direct emission. So during phase II-IV, the decrease value of O₃ signifies that no proper sunlight and heat was present in the region and so O₃ could not be formed properly to escape to cleaner areas and presence of reduced NO₂ couldn't be helped.

The average of 30 days prior to lockdown of NO₂ (µg/m³) concentration across UAs of this region was 42.0 which reduced to 16.7 (reduction of 60%) by the end of lockdown (Figure 7). The highest concentration of NO₂ prior to average of 30 days of lockdown was observed in Patna (60.2) followed by Siliguri (51.2) and Kolkata whereas during entire period of lockdown, highest concentration of NO₂ was in Patna (44.1) followed by Siliguri UA (35.5) and Muzaffarpur (24.1).

Figure 7 Concentration of air pollutants in different phases (both pre-lockdown and lockdown phases)

4.1.6. North-Eastern India

Shillong is one of the major UA in North-Eastern India comprises of 6 states: Arunachal Pradesh, Assam, Meghalaya, Manipur, Tripura, and Nagaland (Table 1). During first phase of lockdown, average concentrations of PM_{2.5}, PM₁₀, SO₂, O₃, and NO₂ (µg/m³) were 42, 66, 7.5,

16.8 and 2.6 that reached to 13.9, 19.4, 8, 11.8 and 2.9 during fourth phases of lockdown (Figure 8), respectively.

Figure 8 Concentration of air pollutants in different region of India

4.2. Regional clustering pattern of air pollutants

As per as result of the clustering analysis, it was well documented that high-high clustering (HH) pattern of air pollutants are concentrated in northern and central regions of India. Particularly the concentrations of particle matter (PM_{2.5} and PM₁₀) remain relatively high in UAs of northern and central India. These are Delhi, Gurugram, Panipath, Sonipath, Yamunagar and Agra. On the other hand, HH clustering pattern of air pollutants have not been observed in other regions of India. For example, during entire phase of lockdown, highest concentration of PM_{2.5} (µg/m³) has been recorded in Delhi (61) followed by Yamunagar (60.8), Pawal (58) and Agra (36). These concentrations of air pollutants in northern and central India was relatively high as compared to other regions. In southern India, highest concentrations of PM_{2.5} (µg/m³) during entire phases of lockdown has been recorded in Kannur (30.85) followed by Hyderabad (30.58), Kozikhode (24.50) and Coimbatore (23.93). Thus from the overall clustering pattern of air pollutants, it is obvious that concentration of air pollutants particularly PM_{2.5} and PM₁₀ were high (high-high clustering pattern) over the UAs located in northern and central India (**Figure 9**).

Figure 9 Cluster maps of air pollutants across the UAs

4.3. Regional pattern of hotspots

The spatial pattern of air pollutants and high concentrations of air pollutants can be presented by hotspot maps. In this study, spatial concentrations of air pollutants over the regions in India have been examined using hotspot analysis. The hotspots (high value of air pollutants) are

concentrated across UAs located in northern and central India. The high value of air pollutants is concentrated in Delhi, Gurugram, Agra, Yamuna Nagar, Panipat, Sonipat etc. The concentration of air pollutants over these UAs remained high during entire periods of lockdown (**Figure 10**).

Figure 10 Hotspot and cold spot maps across the UAs ($PM_{2.5}$, PM_{10} , SO_2 , O_3 and NO_2)

4.4. Regional scenario of air pollution level in India

In this section of study, a composite air quality index (CAQI) has been developed to examine the regional variation of air quality level across UAs of India. The value of CAQI ranges from 0 to 1 where 0 means good air quality to 1 indicates very poor air quality. From the result it was observed that UAs of Northern India during lockdown had relatively lowest air quality (0.47) followed by UAs of Central India (0.45) and Eastern India (0.39) whereas air quality of UAs located in south India had relatively higher value (0.14). **Table 2** lists the categorizations of UAs based on CAQI.

4.5. Statistical Analysis

4.5.1. Coefficient of variation (C_v)

The result of coefficient of variation (C_v) shows that there was a significant variation of air quality in different phase of lockdown across all UAs. During phase I of lockdown, C_v was 36.38 % that reached to 60.84 % during phase IV (increased by 67.23 %). Relatively low C_v during phase I and II clearly suggest that emissions were strictly restricted during these two phases of lockdown and later on emissions were confined in some selected sections of large cities (**Table 3**).

4.5.2. ANOVA analysis

In the present study, analysis of variance (ANOVA) was used to understand the significant differences of spatial concentration of air pollutants over UAs. The result shows that probability

values P for all phases are < 0.05 (**Table 4**). This indicates that there was significant statistical regional difference of air pollutant concentration during different phases of lockdown. The result revealed that air quality of Northern and Central UAs is lowest as compared to Eastern and Southern UAs of India. This clearly suggests that there was significant difference of air pollution level across all regions under considerations of the study during lockdown which is justified by ANOVA analysis.

4.5.3. Correlation analysis

The concentration of air pollutants over UAs in India were investigated using Pearson correlation coefficient (r) in different phases of lockdown. The correlation result of air pollutants during different phases of lockdown is presented in **Supplementary Table 1**. The result revealed that during lockdown, $PM_{2.5}$ had a high positive correlation with PM_{10} ($r = 0.656$ in phase I; $r=0.719$ in phase II; $r=0.717$ in phase III and $r=0.673$ in phase IV). On the other hand, $PM_{2.5}$ had very weak correlation with SO_2 , NO_2 and O_3 during all phases of lockdown.

4.6. Pattern of $PM_{2.5}$ concentration across major UAs in last three years

Analysis of the spatial concentration of air pollutants across the UAs in previous years is essential to understand the impact of lockdown on air quality. In this section, the spatial concentrations of $PM_{2.5}$ across major polluted UAs in last three (2017-2019) has been assessed with same periods of lockdown to examine the impact of lockdown on air pollutant concentrations (**Table 5 4**). Eight UAs have been selected from three regions (Northern, Central and Eastern) and these are most polluted UAs in India as well. In 2017 average concentration of $PM_{2.5}$ ($\mu g/m^3$) in Delhi and Gurugram was 182 in April and 221 in May that declined to 95 (in April) and 99 (May) during the lockdown periods of 2020 in northern India. In case of central India, average concentration of $PM_{2.5}$ across UAs of Agra, Varanasi, Kanpur and Lucknow was 179 and 128 during April and May of 2018, respectively, that reached to 92 in April and 100 in

May of 2020 (**Table 5 4**). Similar result has also been recorded in Patna and Muzaffarpur located in Eastern India. Thus, from the overall analysis, it was well recognized that there was substantial decline of $PM_{2.5}$ across UAs in 2020 during lockdown periods in comparison to previous last three years (2017-2019).

5. Conclusion

From the overall result it was well established that there was substantial improvement of air quality across UAs of India during lockdown period as compared to pre-lockdown period. Decline in concentration of $PM_{2.5}$, PM_{10} , NO, SO_2 (except O_3) were recorded in all the regions of India. Northern UAs had relatively poor air quality among all other regions. More particularly, Panipath, Delhi, and Gurugram had very poor air quality in North India. In Central India too, there was decrease of $PM_{2.5}$ (21%), PM_{10} (12%), NO_2 (47%) and SO_2 (20%) from 30 days' prior lockdown to lockdown. The decline of $PM_{2.5}$ (73%), PM_{10} (38%), NO_2 (52%) and SO_2 (51%) was reported from Western India and in Eastern India, the decrease was $PM_{2.5}$ (65.5%), PM_{10} (28%), NO_2 (60%) and SO_2 (29%). In Eastern India, there were four UAs: Kolkata, Asansol, Siliguri and Patna falling under very poor air quality before lockdown but by the end of lockdown these places shifted towards higher category. In Southern India, $PM_{2.5}$ and PM_{10} was declined by more than 30% and SO_2 and NO_2 were by more than 20%. In North-Eastern India, only one UA: Shillong has decreased of $PM_{2.5}$, PM_{10} , SO_2 , O_3 , and NO_2 by 56.4%, 57.3%, 45.2%, 67.7% and 6.5%, respectively.

From correlation study, it was observed that the correlation of $PM_{2.5}$ is very high with PM_{10} but very weak correlation with SO_2 , NO_2 and O_3 . As per the ANOVA analysis, there were significant differences of air pollution across regions during lockdown. The gap between Northern and Southern region was 0.33. The spatial variation of air pollution level signifies that

there were few polluting pockets where emissions started when local authority withdrawn some of the restrictions after phase III of lockdown.

Author Credit Statement

Author Contributions: Conceptualization and methodology, writing—original draft preparation MD and AD; software, MD, SS; formal analysis, MD, AD and RS; writing—review and editing, RS, SS, PM; All authors have read and agreed to the published version of the manuscript.

Conflict of Interest: None

The following are the supplementary data related to this article.

Supplementary Table 1 Correlation analysis in different phases of lockdown

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Table 1 Selected Urban Agglomeration (UAs) of India

Zones	States	No of states/UTs	No of UAs [considered]
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Zo ne I	Northern	Jammu and Kashmir, Delhi, Haryana, Himachal Pradesh, Punjab, Rajasthan	6	18
Zo ne II	Central	Madhya Pradesh, Uttar Pradesh, Chattisgarh, Uttrakhand	4	14
Zo ne III	Western	Gujrat, Maharastra, Goa	3	7
Zo ne IV	Southern	Tamil Nadu, Karnataka, Andhra Pradesh (undivided) , Kerala	4	11
Zo ne V	Eastern	Bihar, West Bengal, Odisha, Jharkhand, Sikim	5	6
Zo ne VI	North-eastern	Arunachal Pradesh, Assam, Meghalaya, Manipur, Tripura, Nagaland	7	1

Table 2 Categorization of UAs based on CAQI

Air quality level	Ranges	No of UAs	Name of the UAs
Good	< 0.12	7 (12 %)	Western- Pune; Southern- Eluru, Kollam, Kochi, Kozikode, Tirubantapuram, North-Eastern- Shilong
Satisfactory	0.12-0.24	12 (21 %)	Western- Aurangabad, Mumbai; Northern- Jalandhar, Patiala; Southern- Chennai, Coimbatore, Kannur, Mysuru, Tirupati. Central- Sagar, Damoh; Jabba'pur
Moderate	0.24-0.36	10 (18 %)	Western- Ankeshawar, Nagpur, Nashik; Eastern- Kolkata, Asansol; Northern- Ambala, Alwar, Amitswar, Chandigarh; Southern- Hyderabad
Poor	0.36-0.60	20 (35 %)	Western- Ahamedabad; Eastern- Sliguri, Patna, Muzaffarpur; Northern- Yamunagar, Udaipur, Sonipath, Pawal, Karnal, Jaipur, Hishar, Jodhpur, Ajmir; Central- Agra, Muzaffarnagar, Lucknow, Kanpur, Indore, Ratlem, Bhopal
Very poor	>0.60	8 (14 %)	Western- Bhiwandi; Northern- Panipath, Gurugram, Delhi; Central- Varanasi, Meerut, Gwalior, Gaziabad

Table 3 Coefficient of variation in different phases of lockdown

CV (%)					
Phase I	Phase II	Phase III	Phase IV	Overall	Before lockdown
36.38	45.93	58.02	60.84	59.45	53.74

Table 4 Comparison of PM_{2.5} concentrations across major UAs in India during lockdown period of 2020 with same period of 2017-2019

Region	UAs	2017			2018			2019			2020		
		March	April	May	March	April	May	March	April	May	March	April	May
North	Delhi	198.3	86.8	218.6	214.6	123.7	157.7	227.6	163.3	226.5	161.58	110.83	96.87
	Gurugram	186.2	277.9	223.4	185.7	249.8	275.8	142.8	249.0	193.7	97.81	79.17	102.27
Central	Agra	176.9	152.7	134.9	191.9	126.7	161.9	167.8	143.8	121.7	97.06	88.00	98.57
	Varanasi	253.4	192.7	155.2	233.9	71.9	170.8	229.3	201.2	183.6	99.19	64.47	64.80
	Kanpur	150.0	182.0	162.0	130.9	104.7	139.3	118.4	117.2	129.0	107.16	82.27	86.10
	Lucnow	237.7	229.6	153.2	159.6	211.6	247.8	282.6	213.6	129.0	164.52	132.07	154.03
Eastern	Patna	178.0	163.3	57.2	230.1	157.6	141.1	151.3	148.3	107.6	151.42	79.30	56.43
	Muzaffarpur	216.0	120.3	92.5	206.9	111.8	74.1	101.6	110.9	117.4	163.03	78.67	51.70

Graphical abstract

Highlights:

- Air pollution level over the major urban agglomerations (UAs) has been assessed.
- Major improvement of air pollution level during lockdown as compared to pre-lockdown period of 30 days.
- Maximum decline was recorded for NO₂ (about 40%) followed by PM_{2.5} (32%), PM₁₀ (24%) and SO₂ (18%).
- During lockdown, CAQI is 1.00 (signifies most polluted) at Panipat, Gaziabad (0.76), Delhi (0.74), Gurugram (0.72) and Varanasi (0.71).

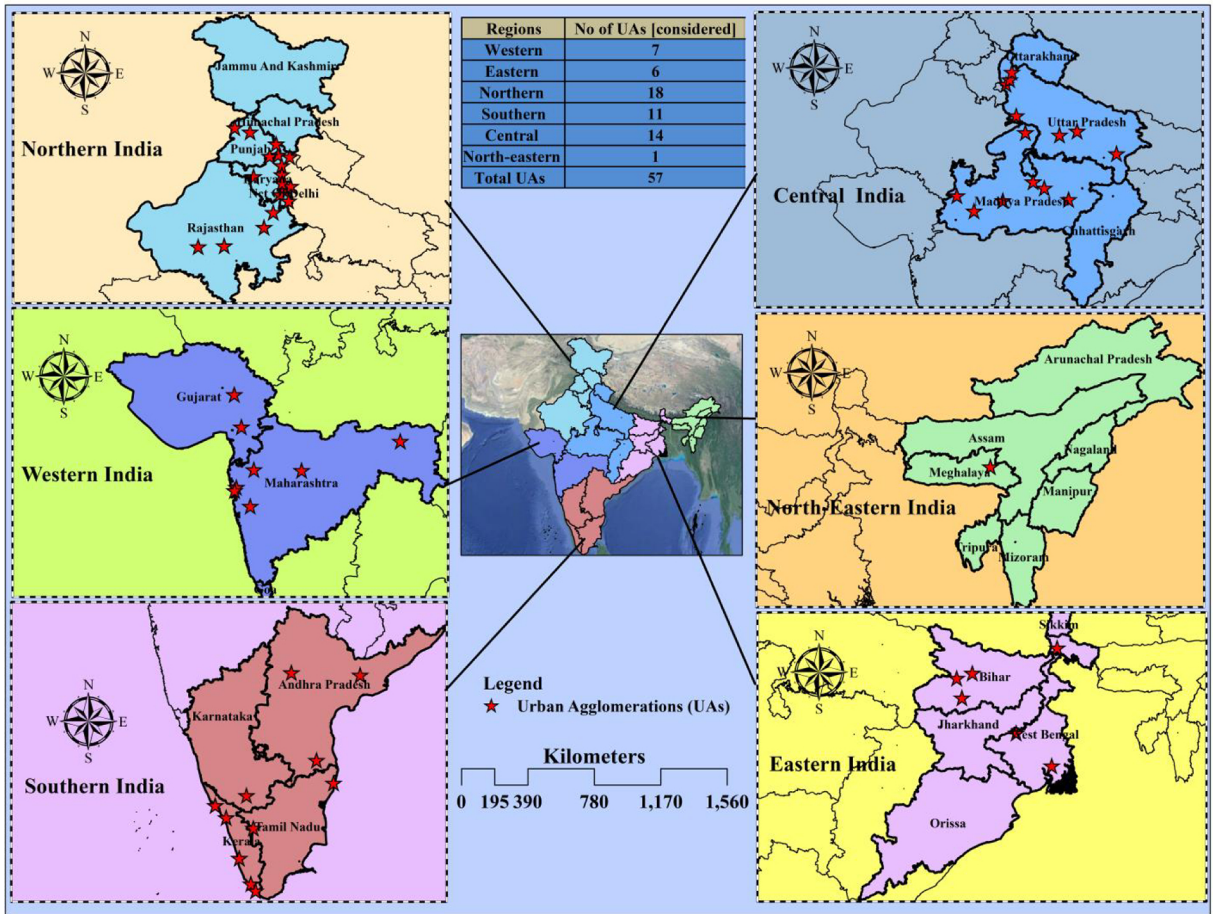


Figure 1

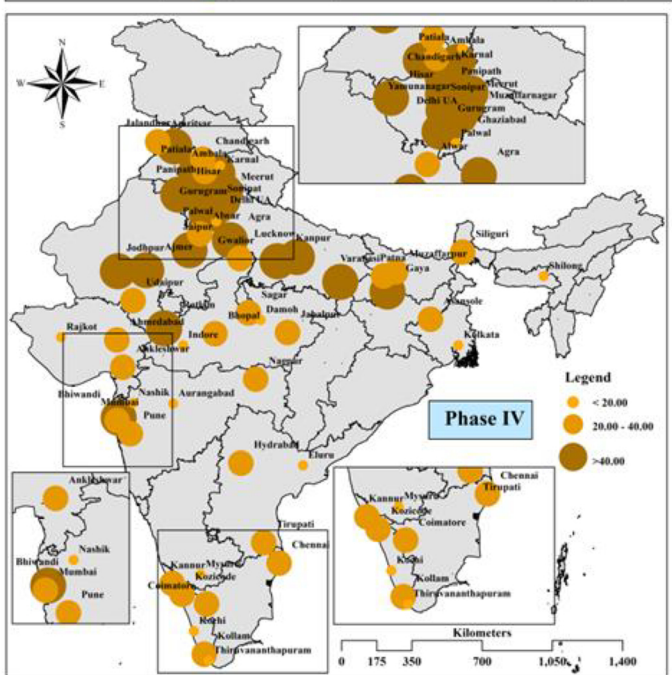
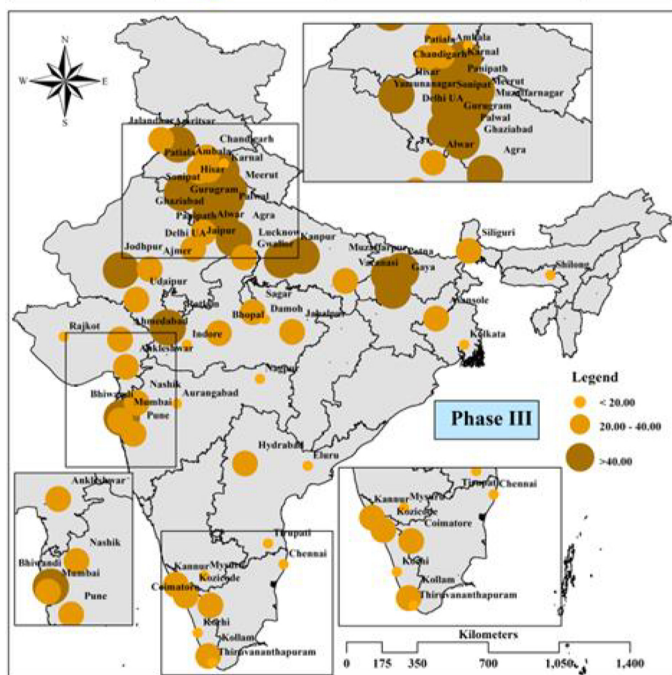
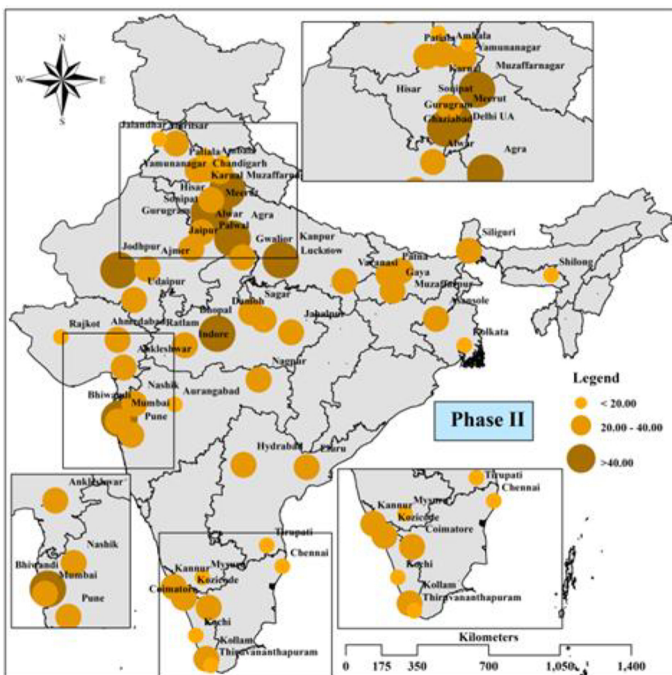
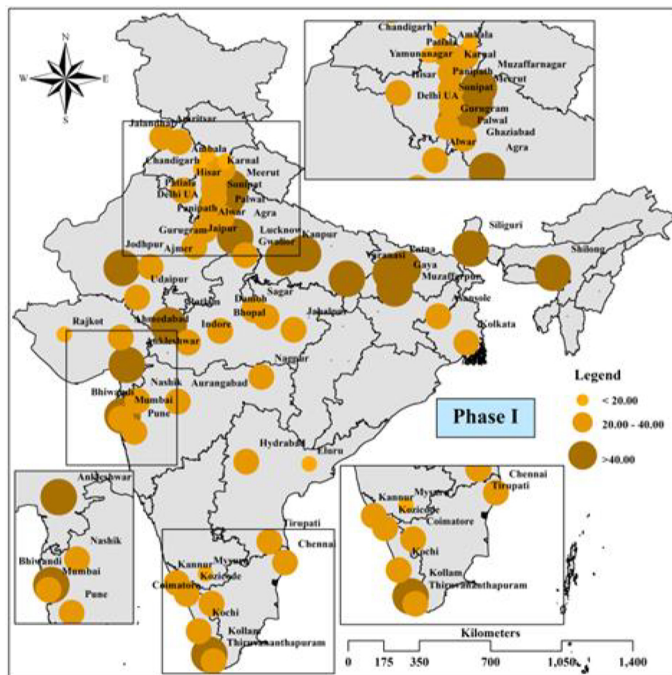


Figure 2

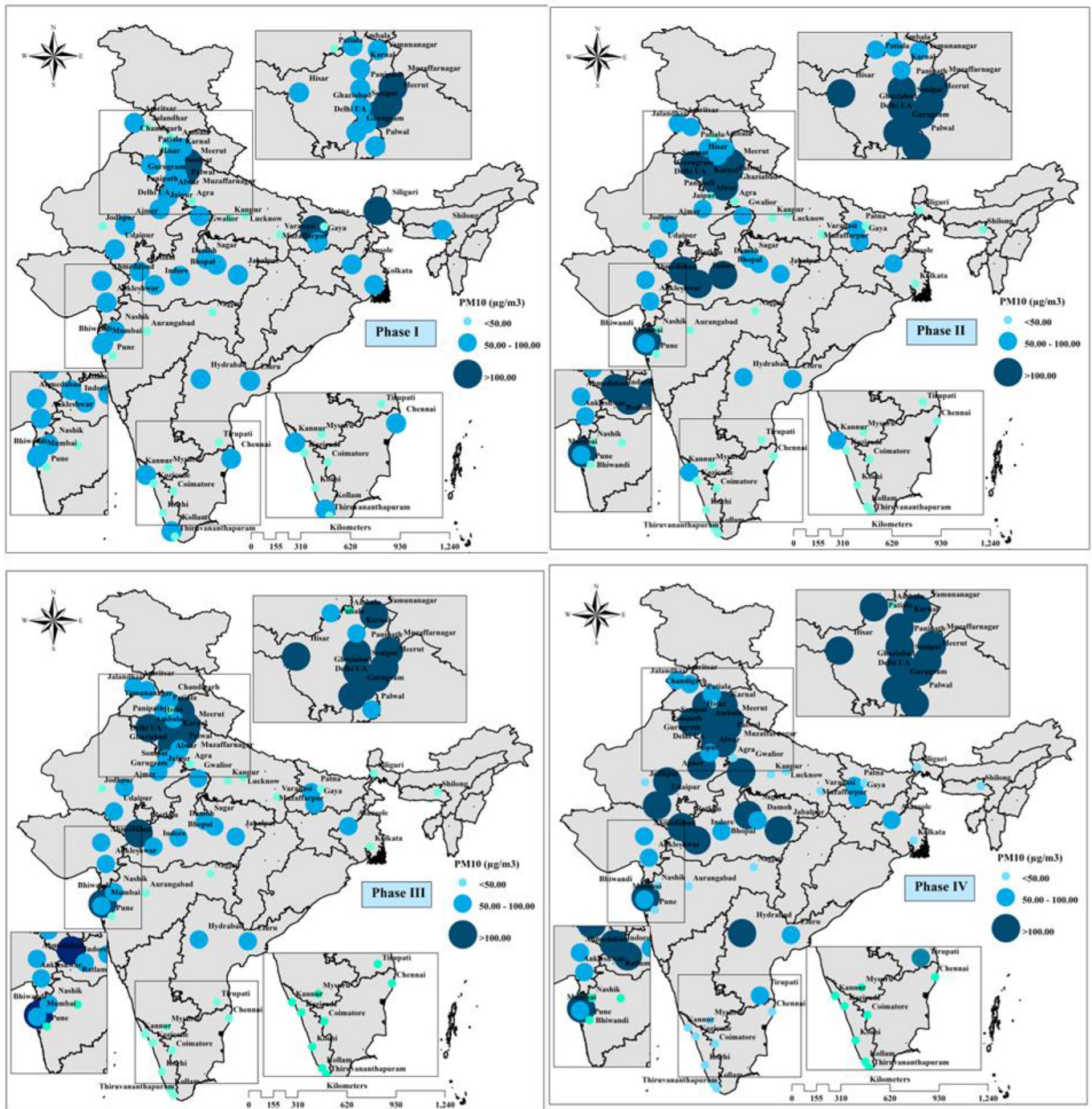


Figure 3

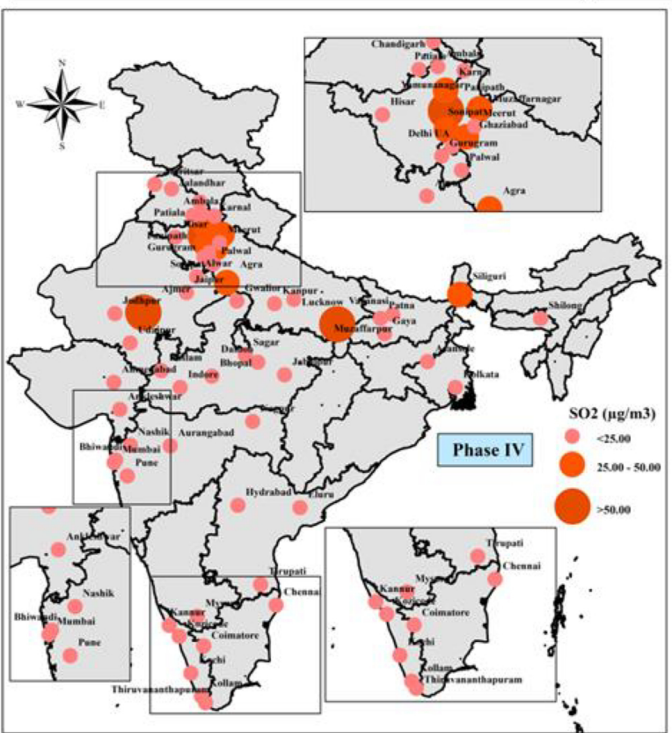
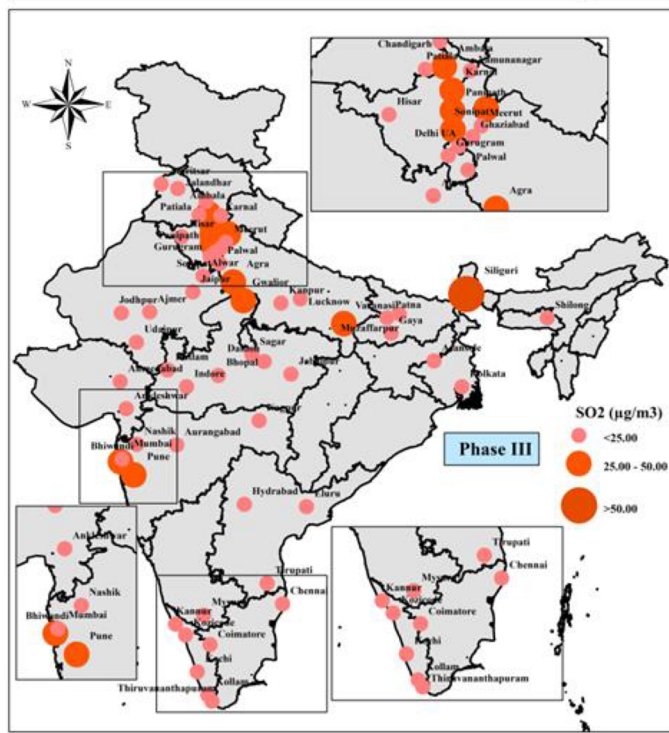
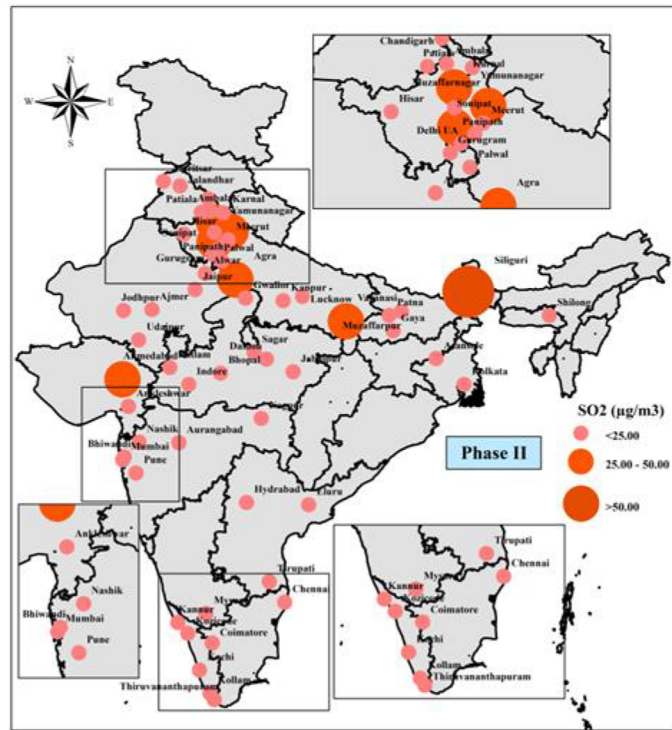
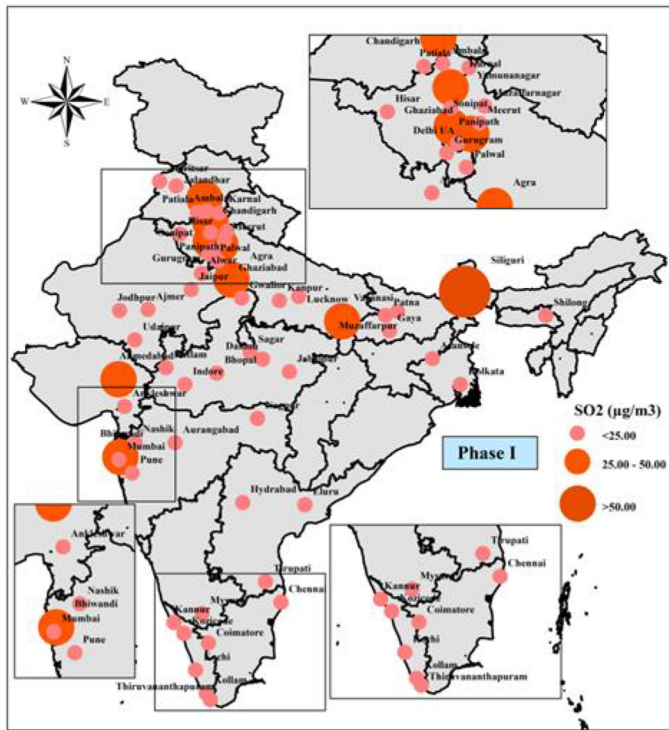


Figure 4

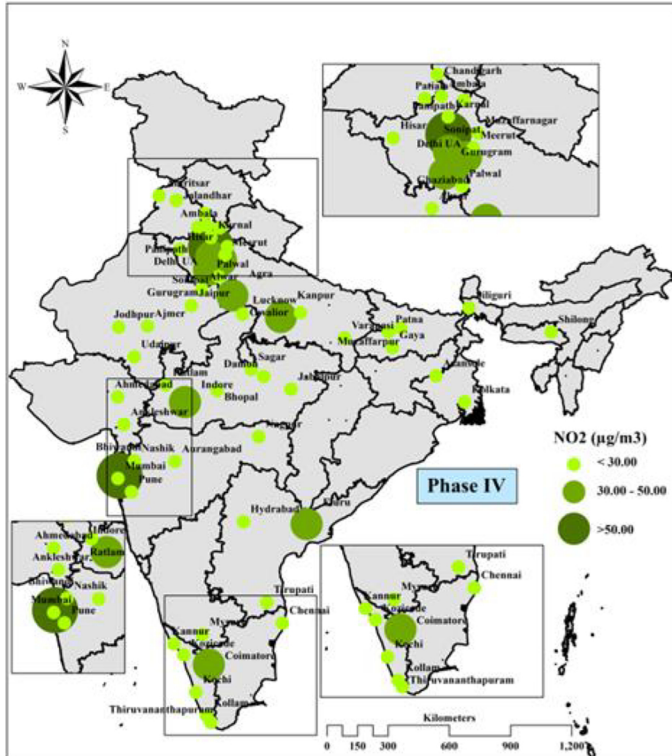
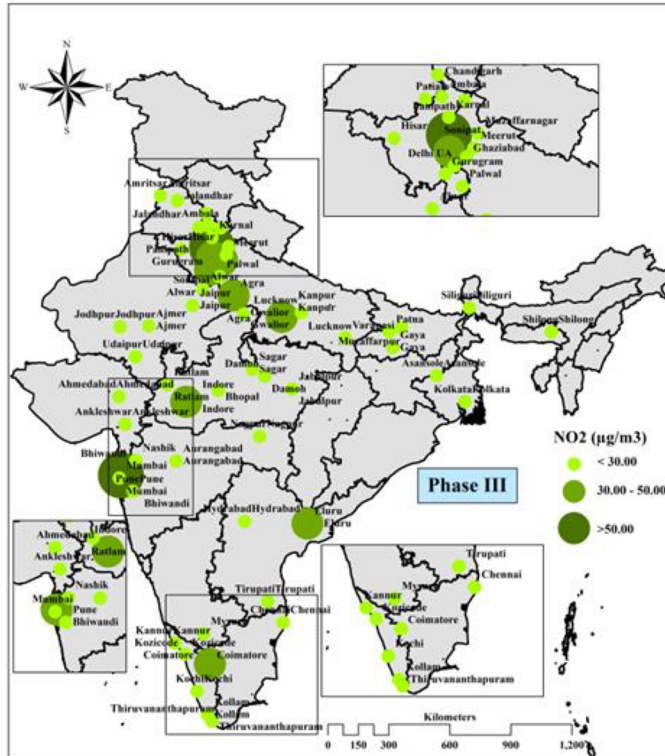
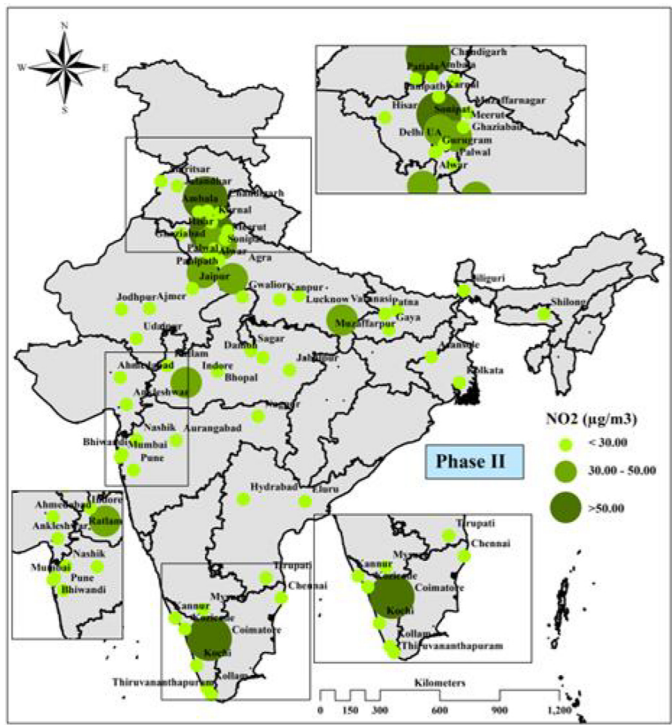
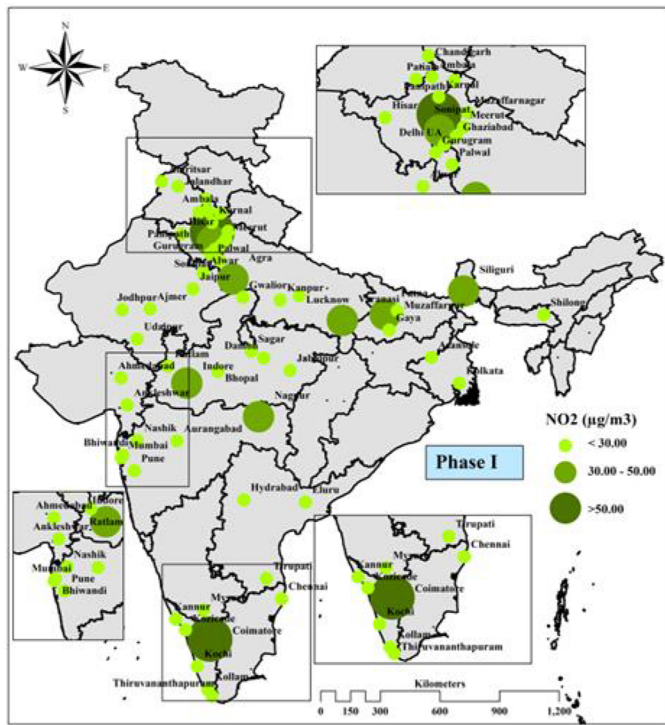


Figure 5

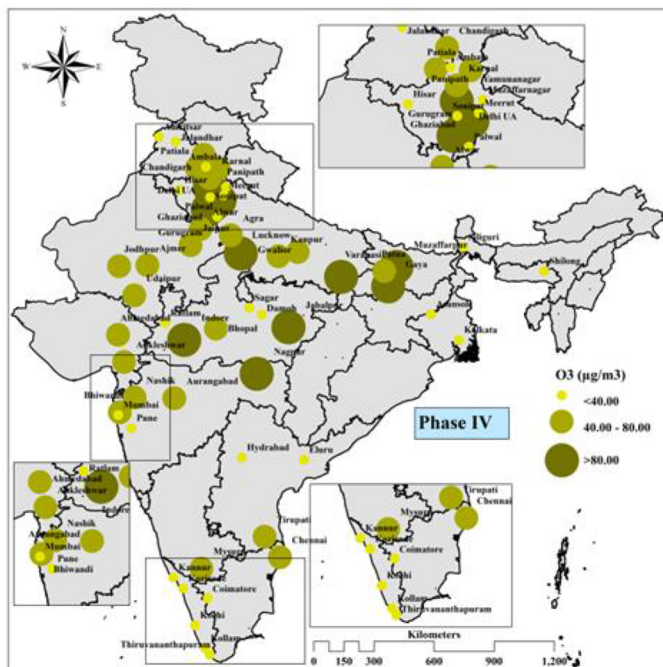
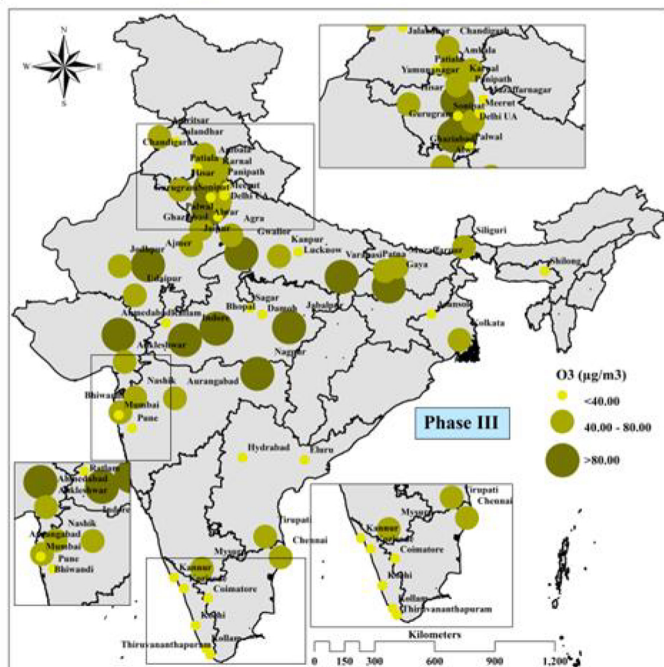
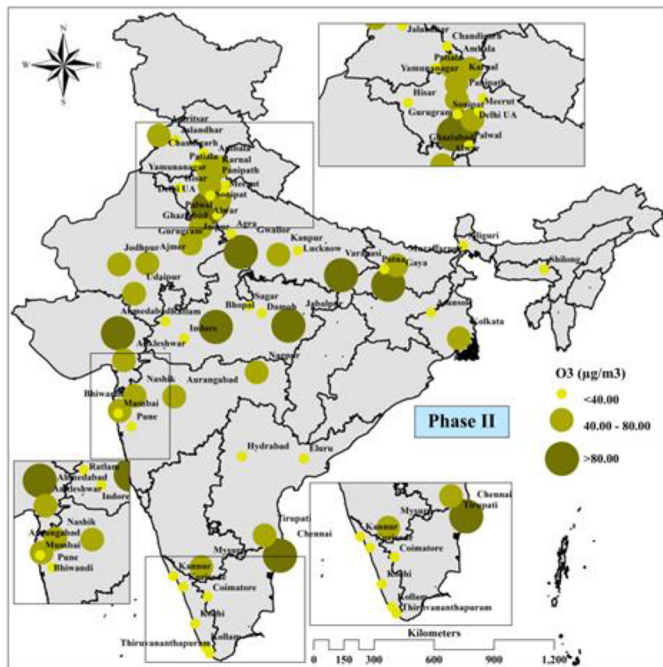
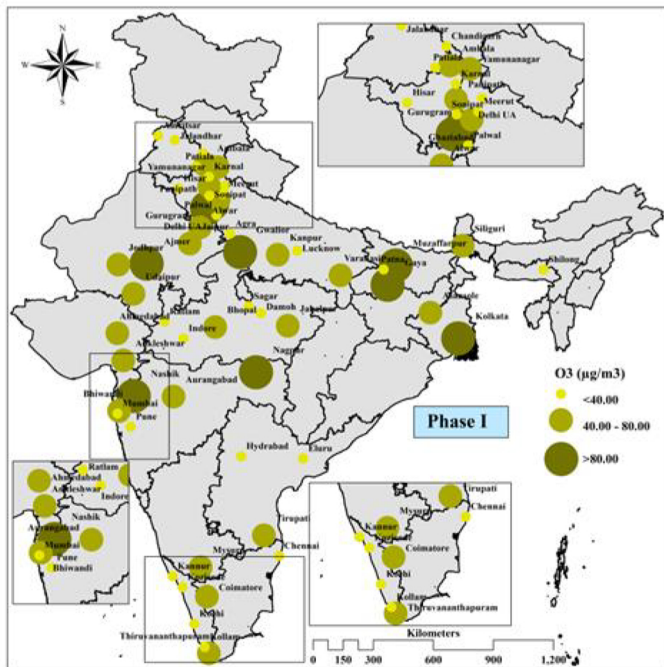


Figure 6

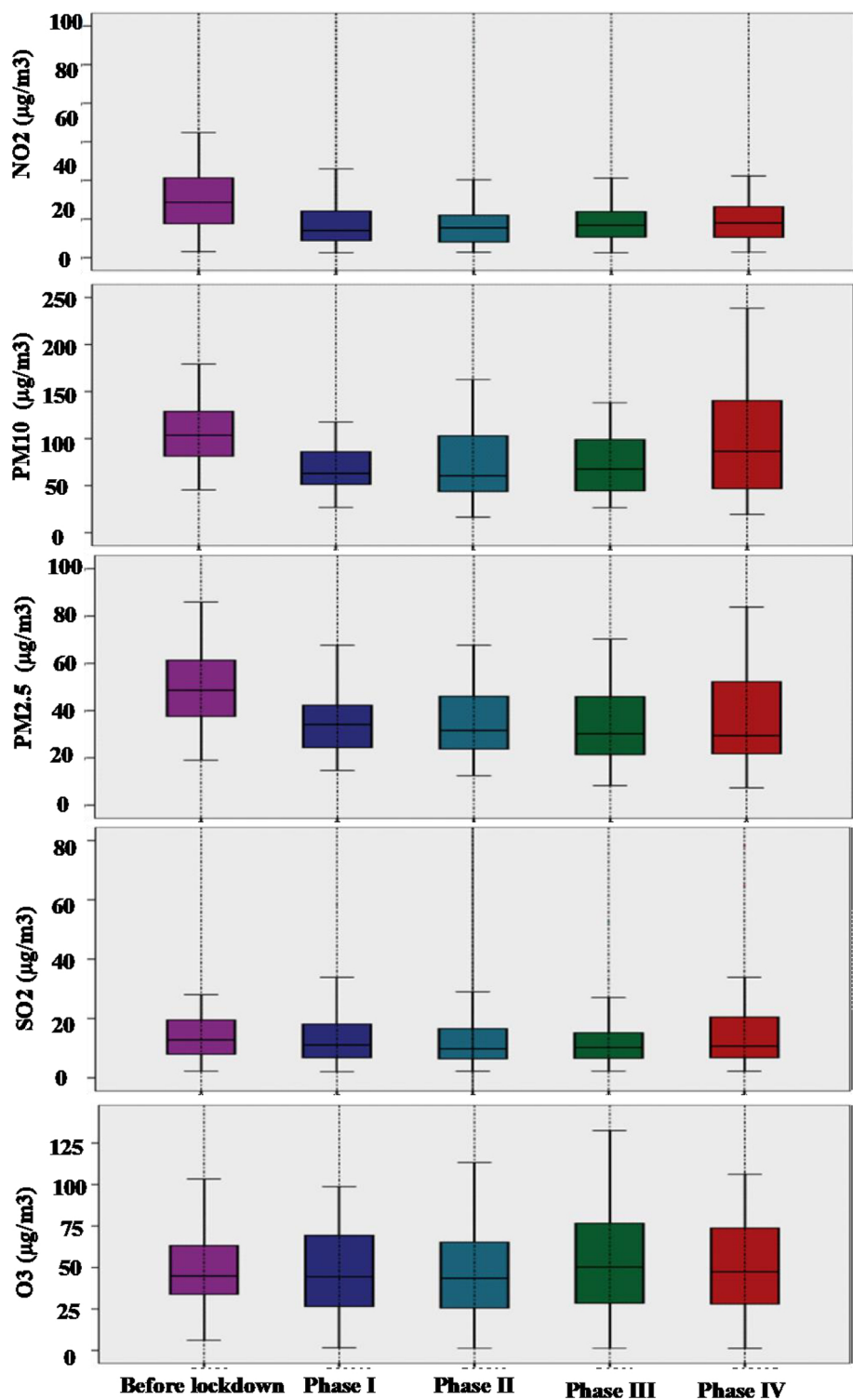


Figure 7

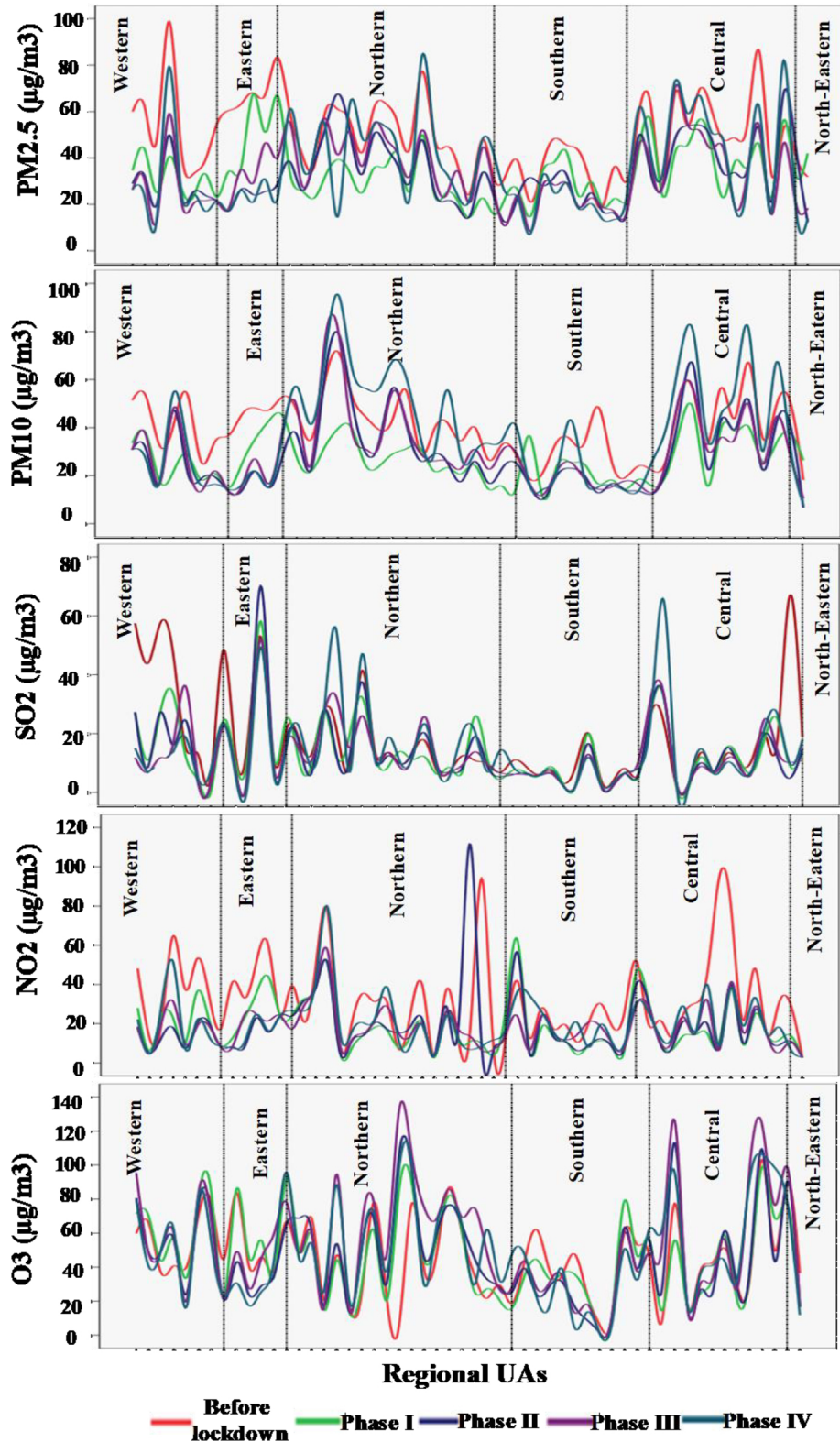


Figure 8

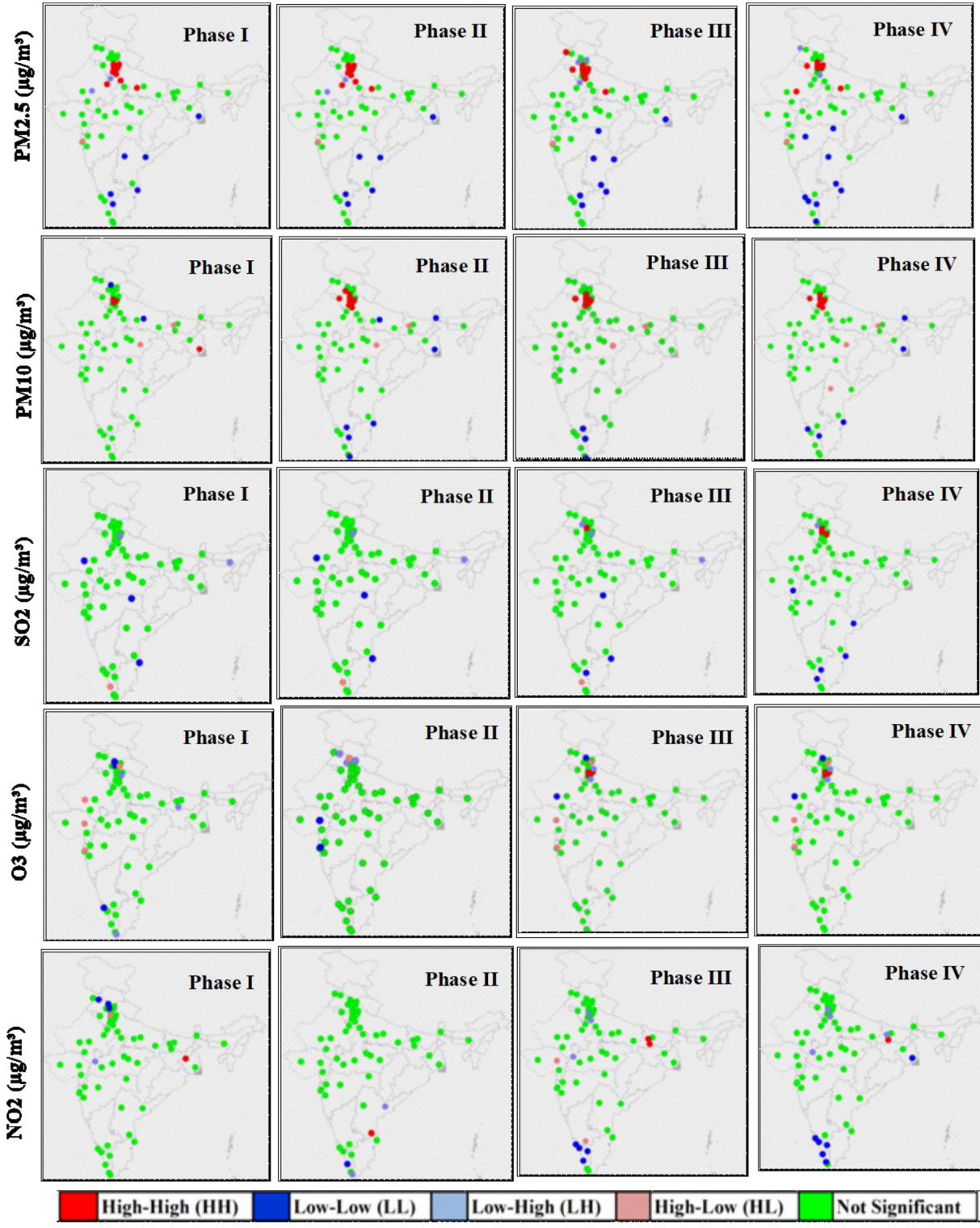


Figure 9

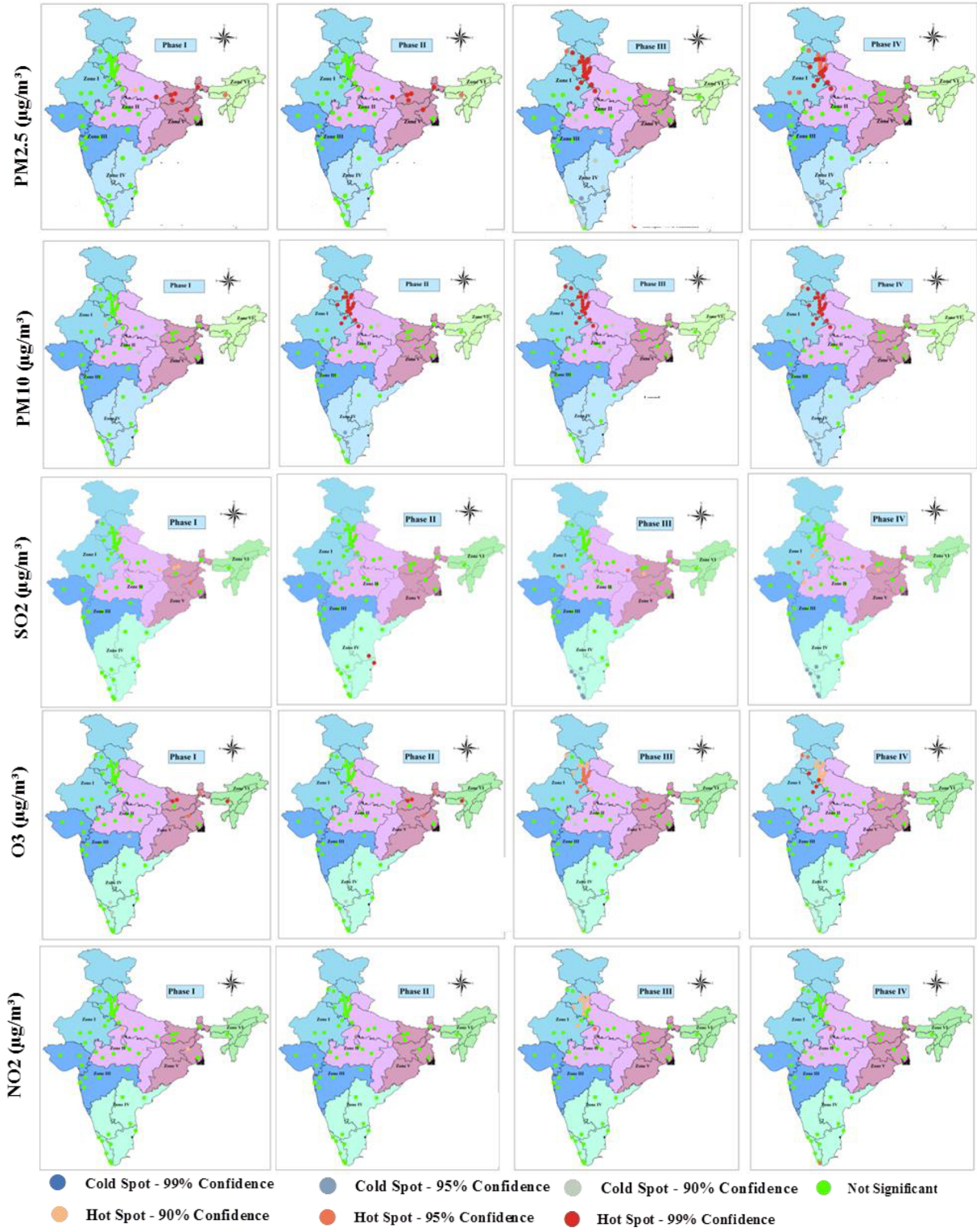


Figure 10