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Establishing a link between fine particulate matter (PM$_{2.5}$) zones and COVID-19 over India based on anthropogenic emission sources and air quality data

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**ABSTRACT**

The spread of coronavirus disease of 2019 (COVID-19) pandemic around the globe is affecting people. The majority of Indian urban complexes are reeling under high emissions of deadly fine particulate matter PM$_{2.5}$ and resulting in poor air quality. These fine particles penetrate deep into the body and fuel inflammation in the lungs and respiratory tract, leading to the risk of having cardiovascular and respiratory problems, including a weak immune system. In the present study, we report the first national-scale study over India, which establishes a strong relationship between the PM$_{2.5}$ emission load and COVID-19 infections and resulting deaths. We find a significant correlation ($R^2 = 0.66 & 0.60$) between the states as well as districts having varied levels of PM$_{2.5}$ emissions with corresponding COVID-19 positive cases respectively, and $R^2 = 0.61$ between wavering air quality on a longer time scale and the number of COVID-19 related deaths till 5 November 2020. This study provides practical evidence that cities having pollution hotspot where fossil fuel emissions are dominating are highly susceptible to COVID-19 cases.

**1. Introduction**

With the beginning of 2020, the whole world is being engulfed by an outbreak of the Severe Acute Respiratory Syndrome Coronavirus 2 (SARS-CoV-2), also called a novel coronavirus disease 2019 (COVID-19). As of 5 November 2020, the world has more than ~53 million confirmed positive corona cases across 215 countries and territories since this pandemic first broke out in China’s Wuhan City (as per Johns Hopkins Coronavirus Resource Center & covid19india.org). This unstoppable novel coronavirus infection apparently in due course can lead to acute respiratory distress syndrome (ARDS) or fatal pneumonia (Conticini et al., 2020; Lu et al., 2020; Zhu et al., 2020). COVID-19 is considered a health disaster across the globe with more than 1.25 million deaths as of 5th November 2020 where the main route of human-to-human transmission of COVID-19 is through respiratory droplets (Pattorini and Regoli, 2020; Lu et al., 2020). Most COVID-19 affected countries adopted social distancing measures as an effective tool to curb the transmission of infection and reduce the impact of the novel virus. COVID-19 affects the upper respiratory and lungs, notably, so people residing in the

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polluted atmosphere could be more vulnerable and become a matter of great concern for countries with poor air quality (Conticini et al., 2020; Cao et al., 2020).

Air pollution is the fifth leading cause of mortality across the globe. Air pollution-related death are associated with lung disease (23%), cardiovascular (19%), ischemic (24%), stroke (21%) (Global Burden of Disease Study, 2016a; Global Burden of Disease Study, 2016b; WHO, 2019; Brunekreef and Holgate, 2002). Since the last three decades, the most dominating traditional mechanism of incomplete combustion of fuel like wood, dung and straw have been replaced by fossil fuel-based complete combustion in industrial, thermal power plants and transport (Kioumourtzoglou et al., 2016), leading to the release of finer aerosol particles, known as Particulate Matter with diameter less than or equal to 2.5 μm (PM$_{2.5}$) into the ambient atmosphere (Feng et al., 2016). In metropolitan areas, PM$_{2.5}$ emission has brought global attention (Gong et al., 2012). Epidemiological and toxicological studies have highlighted the harmful effect of PM$_{2.5}$ that can penetrate deeper into the bloodstream and lungs (Feng et al., 2016; Delfino et al., 2005; Atkinson et al., 2010; Raaschou-Nielsen et al., 2013). Prolonged exposure to such pollutants could prompt a persistent change of the immune system, so pollutants undermine the first line of defence of the upper respiratory tract (Tsai et al., 2019; Cao et al., 2020; Ciencewicki and Jaspers, 2007). The PM$_{2.5}$ is particularly deadly (Horne et al., 2018; Raaschou-Nielsen et al., 2013). Even without a pandemic, studies have established that exposure to PM$_{2.5}$ over long periods could have an adverse impact on health in terms of lung disease like

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**Fig. 1.** Political Map of Indian States, Districts, IGP region & AQMS location.
acute respiratory inflammation, chronic obstructive pulmonary disease (COPD) and asthma (Feng et al., 2016; Delfino et al., 2005; Raaschou-Nielsen et al., 2013). Its detrimental effects could escalate the pandemic further because one recent study has established that the air sample taken from the COVID-19 patient's room has viral contamination (Report of the WHO-China Joint Mission on Coronavirus Disease, 2019).

The virus could spread through the air where PM$_{2.5}$ can act as a “carrier or condensation nuclei” to which virus droplets attach could remain in the air for a certain time (Domingo et al., 2020; Fattorini and Regoli, 2020; Feng et al., 2016). Recent studies have confirmed the linkage between COVID-19 and PM$_{2.5}$ (Wu et al., 2020; Ogen, 2020; Fattorini and Regoli, 2020; Frontera et al., 2020; Domingo et al., 2020). The results are advocating that a person living for decades in a region having PM$_{2.5}$ level above the permissible limit is likely to have a 15% more chance to die of COVID-19 than a person in another area with one unit less PM$_{2.5}$ (Dutheil et al., 2020; Chen et al., 2013). Conticini et al. (2020) confirm a correlation between COVID-19 and atmospheric pollution over Italy. The research highlights that Lombardy and Emilia Romagna regions in Northern Italy are experiencing the highest case of lethality in the world due to COVID-19 and are considered as one of Europe's most polluted areas.

The take-home messages from the above research findings are alarming for India, where prominent PM$_{2.5}$ is responsible for deteriorating air quality in most cities. India, being the second most populous country in the world, requires further studies in this direction as how the air pollutants, especially PM$_{2.5}$, is linked to the ongoing COVID-19 pandemic. Moreover, twenty-one out of thirty world’s most polluting cities belong to India and have attracted global attention recently (WMO, 2018). The present study is the first of its kind to evaluate the relation between PM$_{2.5}$ emission loads through newly developed national emission inventory of PM$_{2.5}$ for 2019 and COVID-19 positive cases in India as of 5th November 2020. To strengthen the analysis further, we compare COVID-19 data with Air Quality Index (AQI) data collected from a network of 16 Air Quality Monitoring Station (AQMS) sites across the country under the System of Air Quality and Weather Forecasting (SAFAR) and Monitoring of Air Pollutant and Network (MAPAN), Ministry of Earth Sciences (MoES) programs.

2. Materials and methods

The area of interest (AOI) in the present study is India, which is subdivided into 36 states (further divided into 721 districts). The political map of Indian States and districts along with the Indo-Gangetic-plain (IGP) region is being highlighted along with the location of AQMS stations across the country (Fig. 1).

The present analysis is supported by three kinds of data sets i.e. a) National Emission Inventory (NEI) of PM$_{2.5}$ for 2019, developed by us, b) Number of COVID-19 positive case and corresponding death as of 5th November 2020 adopted from Govt. of India website (http://mohfw.gov.in), and c) Air quality index data (in-situ observations) collected for 16 stations across the country.

Present analysis needs the development of a reliable high-resolution gridded (10 km × 10 km) inventory to assess a load of PM$_{2.5}$ emission from both fossil and biomass-based anthropogenic activities and natural sources. The development of emission inventory is a complex process and needs spatial and temporal activity dataset. The first step towards developing emission inventory is to identify all possible major/minor anthropogenic and natural sources responsible for both in-door and out-door air pollution. In the present work, a widely used bottom-up approach has been adopted here to improve the emission estimation using a methodology as per IPCC (Intergovernmental Panel on Climate Change) approach (Sahu et al., 2011; Beig et al., 2019; Bond et al., 2004). The gridded level PM$_{2.5}$ estimation was carried out by incorporating primary/secondary fuel activity data collected for 17 sectors like transport, industry, thermal power, open waste burning, waste incineration, brick-kiln, aviation sector, crop residue burning, construction, cow dung, street vendor, agricultural diesel generator set, crematory, windblown road dust under anthropogenic sources responsible for outdoor air pollution and cigarette smoking, household cooking in slums and residential, mosquito coils, incense sticks for worship as a source of indoor air pollution. The activity data used in the present study is summarized as additional tables (i.e. Table 3, 4, 5, 6).

To calculate the total emissions of a particular pollutant from all above sources, method for various sectors are adopted by us (Sahu et al., 2011; Sahu et al., 2014; Sahu et al., 2017) which are also described in detail by Bond et al. (2004) and Klimont et al. (2002). Equations adopted for the estimation of total emission is in accordance with the following:

\[
TE = \sum_r \sum_s \sum_t FU_{r,s,t} \left[ \sum_l EF_{r,s,t,l} A_{r,s,t} \right]
\]

(1)

where, \(r, s, t\) = sector, fuel type, technology; \(TE\) = Total Emission; \(FU\) = Sector and fuel specific amount; \(EF\) = Technology specific EFs; \(A\) = fraction of fuel for a sector with particular technology where \(\sum A = 1\) for each fuel and sector.

The emission from transport sector specifically has been calculated as per the following equation by adopting technology specific vehicular emission factors for transport sector of India. (ARAI, 2007; CPCB, 2010).

\[
E_v = \sum(Vh_i \times D_i) \times EF_{i,km}
\]

(2)

where, \(E_v\) = Total Emission of compound; \(Vh_i\) = Number of Vehicle per category; \(D_i\) = Distance travelled in a year per different vehicle type; \(EF_{i,km}\) = emission of compound, vehicle type per driven kilometer.

Wind-blown road dust due to vehicle movement on paved and unpaved roads is figured out to be one of the major sources of PM. So, the following eqs. 3 and 4 denote the dust load estimations.

For Paved Road Dust
\[ E_p = \left[ k \left( \frac{st}{2} \right)^{0.91} (wt)^{1.02} \right] \left( 1 - \frac{pt}{4N} \right) \] (3)

where, \( E_p \) = particulate emission factor (having units matching the units of \( k \)); \( k \) = particle size multiplier for particle size range and units of interest; \( st \) = road surface silt loading (grams per square meter) (g/m\(^2\)); \( wt \) = average weight (tons) of the vehicles travelling on the road; \( pt \) = number of “wet” days with at least 0.254 mm (0.01 in) of precipitation during the averaging period; \( N \) = number of days in the averaging period (e.g., 365 for annual, 91 for seasonal, 30 for monthly).

For Unpaved Road Dust

\[ E_{up} = \left\{ k \left( \frac{st}{12} \right)^{a} \left( \frac{VS}{30} \right)^{d} \left( \frac{m}{0.5} \right)^{c} \right\} \left( \frac{365 - pt}{365} \right) \] (4)

Where, \( E_{up} \) = size-specific emission factor (lb/VMT); \( st \) = surface material silt content (%); \( m \) = surface material moisture content (%); \( VS \) = mean vehicle speed (mph); \( C \) = emission factor for 1980’s vehicle fleet exhaust, brake wear and tire wear; \( pt \) = number of days in a year with at least 0.254 mm (0.01 in) of precipitation; \( k, a, c \) and \( d \) are empirical.
Table 1
Demonstrating PM$_{2.5}$ Emission load across 36 states and union territories in India.

| Sl. No. | State/Union Territories          | PM$_{2.5}$ Emission (Gg/Yr) | COVID-19 Cases |
|---------|----------------------------------|------------------------------|----------------|
| 1       | Andaman & Nicobar islands        | 2.07                         | 4450           |
| 2       | Andhra pradesh                   | 294.81                       | 842,967        |
| 3       | Arunachal pradesh                | 26.38                        | 15,398         |
| 4       | Assam                            | 122.05                       | 208,787        |
| 5       | Bihar                            | 549.87                       | 222,612        |
| 6       | Chandigarh                       | 8.14                         | 15,134         |
| 7       | Chhattisgarh                     | 220.12                       | 200,937        |
| 8       | Dadra & Nagar Haveli             | 2.88                         | 1594           |
| 9       | Daman & Diu                      | 0.57                         | 1675           |
| 10      | Delhi                            | 145.69                       | 438,529        |
| 11      | Goa                              | 16.32                        | 45,065         |
| 12      | Gujarat                          | 482.53                       | 180,699        |
| 13      | Haryana                          | 330.15                       | 182,804        |
| 14      | Himachal Pradesh                 | 60.44                        | 25,486         |
| 15      | Jammu & Kashmir                  | 109.41                       | 105,701        |
| 16      | Jharkhand                        | 190.67                       | 104,442        |
| 17      | Karnataka                        | 504.02                       | 846,887        |
| 18      | Kerala                           | 169.95                       | 486,110        |
| 19      | Lakshadweep                      | 0.01                         | 0              |
| 20      | Madhya Pradesh                   | 581.49                       | 177,361        |
| 21      | Maharashtra                      | 828.35                       | 1,719,858      |
| 22      | Manipur                          | 17.31                        | 20,376         |
| 23      | Meghalaya                        | 17.59                        | 10,202         |
| 24      | Mizoram                          | 8.85                         | 3090           |
| 25      | Nagaland                         | 20.59                        | 9474           |
| 26      | Odisha                           | 260.4                        | 301,574        |
| 27      | Puducherry                       | 5.5                          | 35,838         |
| 28      | Punjab                           | 384.24                       | 137,445        |
| 29      | Rajasthan                        | 541.33                       | 211,310        |
| 30      | Sikkim                           | 40.05                        | 4245           |
| 31      | Tamil Nadu                       | 482.36                       | 743,822        |
| 32      | Telangana                        | 264.77                       | 250,331        |
| 33      | Tripura                          | 13.66                        | 31,514         |
| 34      | Uttar Pradesh                    | 1138.08                      | 497,563        |
| 35      | Uttar Pradesh                    | 68.47                        | 65,279         |
| 36      | West Bengal                      | 378.17                       | 405,314        |
|         | Total                            | 8251.29                      | 8,553,864      |

a Number of COVID-19 cases is high due to rescue of positive cases from special operation

Table 2
Demonstrating Air Pollution Index (API) data along with corresponding district level COVID-19 data.

| Sl. No. | AQMS Cities | Number of Days above National Ambient Air Quality Standards (NAAQS) | Total Bad Air Quality Days | COVID-19 Cases | COVID- 19 Death Cases |
|---------|-------------|---------------------------------------------------------------------|-----------------------------|----------------|----------------------|
|         |             | Moderate | Poor | Very Poor | Severe |                     |                             |                             |                             |                     |
| 1       | Ahmedabad   | 121      | 55   | 9         | NA     | 185                  | 43,923                       | 1919                        |                             |                     |
| 2       | Aizwal      | 15       | 4    | 4         | NA     | 23                   | 2171                         | 2                           |                             |                     |
| 3       | Bangalore   | 35       | 4    | NA        | NA     | 39                   | 365,959                       | 4086                        |                             |                     |
| 4       | Bhubaneswar | 50       | 8    | NA        | NA     | 58                   | 49,887                       | 258                         |                             |                     |
| 5       | Chennai     | 60       | NA   | NA        | NA     | 60                   | 207,197                       | 3713                        |                             |                     |
| 6       | Delhi       | 109      | 7    | 3         | 95     | 288                  | 438,529                       | 6989                        |                             |                     |
| 7       | Guwahati    | 73       | 7    | 4         | NA     | 84                   | 4590                         | 30                          |                             |                     |
| 8       | Hyderabad   | 37       | 4    | 4         | 29     | 74                   | 79,215                        | 23                          |                             |                     |
| 9       | Jabalpur    | 37       | NA   | NA        | NA     | 37                   | 13,029                       | 211                         |                             |                     |
| 10      | Mumbai      | 88       | 55   | 22        | NA     | 165                  | 264,545                       | 10,445                      |                             |                     |
| 11      | Pune        | 113      | 4    | NA        | NA     | 117                  | 338,583                       | 7060                        |                             |                     |
| 12      | Srinagar    | 41       | 20   | 40        | 44     | 145                  | 20,413                        | 375                         |                             |                     |
| 13      | Tezpur      | 18       | 11   | 11        | NA     | 40                   | 2548                         | 14                          |                             |                     |
| 14      | Trivendrum  | 36       | 4    | NA        | NA     | 40                   | 63,490                        | 448                         |                             |                     |
| 15      | Udaipur     | 40       | 7    | NA        | NA     | 47                   | 7200                         | 75                          |                             |                     |
| 16      | Visakhapatnam | 40    | 7    | 4         | NA     | 51                   | 56,775                        | 517                         |                             |                     |
constants. Towards the development of gridded emission inventory, two most sensitivity parameters are emission factors and activity data. We have summarized the used data and sources as supplementary information.

### Table 3
Technological Emission factors used for transport sector.

| Emission Factors | 2 W | 3 W (CNG) | 3 W (Diesel) | Buses (Petrol) | C Cars (CNG) | C Cars (Diesel) | HCV | LCV | MSLV |
|------------------|-----|-----------|--------------|----------------|--------------|----------------|-----|-----|-------|
| (g/km)           | 2 W | 3 W       | 4 W          | 2S             | 3 S          | 4S             |     |     |       |
| 5 yr             | 0.015 | 0.118   | 0.015 | 0.044 | 0.795 | 0.002 | 0.001 | 0.015 | 1.240 | 0.475 | 1.240 |
| 10 yr            | 0.035 | 0.118   | 0.011 | 0.044 | 1.213 | 0.005 | 0.002 | 0.125 | 1.965 | 0.655 | 1.965 |
|                  |      |          |            |                |              |                |     |     |       |

Source: ARAI, Air Quality Monitoring Project-Indian Clean Air Program, 2007 report/ CPCB 2010 Report/ Sahu et al. (2011) Where; 2 W – Two wheelers, 3 W- Three Wheelers (2S- Two Stroke, 3S- Three Stroke), P Cars- Personal Cars, C Cars- Commercial Cars, HCV- Heavy Commercial Vehicle, LCV- Light Commercial Vehicle, MSLV- Miscellaneous Vehicles.

### Table 4
Technological emission factors for all other sectors.

| Sector                        | Fuel         | PM$_{2.5}$ Emission Factors | Unit |
|-------------------------------|--------------|-----------------------------|------|
| Power Plant                   | Coal/Lignite | 0.60 (Sahu et al., 2017)    | g/kg |
| Industry                      | Coal/Coke    | 1.84 (Beig et al., 2018)    | g/kg |
| Residential                   | LPG          | 0.33 (Reddy and Venkataraman, 2002) | g/kg |
|                               | Wood         | 12.24 (Reddy and Venkataraman, 2002) | g/kg |
|                               | Coal         | 12.2 (Reddy and Venkataraman, 2002) | g/kg |
|                               | Kerosene     | 1.9 (Reddy and Venkataraman, 2002) | g/kg |
|                               | Cow-dung     | 5.04 (Reddy and Venkataraman, 2002) | g/kg |
| Slum                          | LPG          | 0.33 (Reddy and Venkataraman, 2002) | g/kg |
|                               | Wood         | 12.24 (Reddy and Venkataraman, 2002) | g/kg |
|                               | Coal         | 12.2 (Reddy and Venkataraman, 2002) | g/kg |
|                               | Kerosene     | 1.9 (Reddy and Venkataraman, 2002) | g/kg |
|                               | Cow-dung     | 5.04 (Reddy and Venkataraman, 2002) | g/kg |
| Street Vendor                 | LPG          | 0.33 (Reddy and Venkataraman, 2002) | g/kg |
|                               | Wood         | 12.24 (Reddy and Venkataraman, 2002) | g/kg |
|                               | Coal         | 12.2 (Reddy and Venkataraman, 2002) | g/kg |
|                               | Kerosene     | 1.9 (Reddy and Venkataraman, 2002) | g/kg |
| Incense sticks                | Biomass      | 7.931 (Beig et al., 2018)    | g/kg |
|                               | Charcoal     | 12.2 (Reddy and Venkataraman, 2002) | g/kg |
|                               | Resin        | 33.95 (Cohen et al., 2013)   | g/kg |
|                               | Bakhoor      | 153.72 (Cohen et al., 2013)  | g/kg |
| Mosquito Coils                | Biomass      | 7.931 (Beig et al., 2018)    | g/kg |
|                               | Charcoal     | 12.2 (Reddy and Venkataraman, 2002) | g/kg |
|                               | Wood Dust    | 12.24 (Reddy and Venkataraman, 2002) | g/kg |
| Cigarettes                    | Tobacco      | 21.60 (EMEP/EEA air pollutant emission inventory guidebook, 2016) | g/kg |
| Crematory                     | Wood         | 12.24 (Reddy and Venkataraman, 2002) | g/kg |
| Municipal Solid-waste Burning | NA           | 13.00 (Sharma et al., 2019)  | g/kg |
| Municipal Solid-waste Incineration Plant | NA | 18.3 (Emission Inventory Guidebook, 1999) | kg/t |
| Brick Kiln                    | Coal         | 12.2 (Reddy and Venkataraman, 2002) | g/kg |
|                               | Biomass      | 7.931 (Reddy and Venkataraman, 2002) | g/kg |
|                               | Rubber       | 24.48 (Beig et al., 2018)    | g/kg |
| Diesel Generator Set          | Diesel       | 9 (Beig et al., 2018)        | g/KW-h |
| Crop Residue Burning          | Rice         | 8.3 (Khaiwal et al., 2019)   | g/kg |
|                               | Wheat        | 7.6 (Khaiwal et al., 2019)   | g/kg |
|                               | Sugarcane    | 3.8 (Khaiwal et al., 2019)   | g/kg |
|                               | Cotton       | 5.9 (Khaiwal et al., 2019)   | g/kg |
|                               | Coarse Cereals| 4.1 (Zhang et al., 2019)    | g/kg |
|                               | Mustard      | 7.8 (Beig et al., 2018)      | g/kg |
|                               | Groundnut    | 7.9 (Beig et al., 2018)      | g/kg |
|                               | Maize        | 7.9 (Beig et al., 2018)      | g/kg |
| Bio-Fuel (Cow Dung Cake)      | Cow-dung     | 5.04 (Reddy and Venkataraman, 2002) | g/kg |
|                               | Wood         | 12.24 (Reddy and Venkataraman, 2002) | g/kg |

3. Results and discussion

Fig. 2 (a) depicts the spatial distribution of gridded PM$_{2.5}$ emission from all anthropogenic and natural sources in India, where the total emission is found to be 8251 Gg/year (2019). The relative contribution of various sectors is represented in the form of a pie chart given in Fig. 2 (b). The high PM$_{2.5}$ emission of the order of 10–100 tons/day is found over Western, Southern, North-Western, Indo-Gangetic Plain (IGP) of India which is encompassed by comparatively developed and more industrialized states like Maharashtra, Punjab, Gujarat, Kerala, Tamil Nadu, Haryana, Uttar Pradesh, Karnataka. It is noticed that the gridded hotspots are confined over
industrial regions and large cities in these states, where fossil fuel is dominating sources as compared to bio-fuel. In cities, transport and industries are major sources of PM$_{2.5}$ due to complete combustion. A comparatively moderate PM$_{2.5}$ emission of the magnitude 1–6 tons/day is restricted over Indo-Gangetic-Plain (IGP) followed by low emission of the order of 0-1 tons/day is confined over major parts of Eastern, Central, and North-Eastern India. In IGP, biofuel is being widely used by the rural population. When the gridded PM$_{2.5}$ emissions are superimposed by district (sub-division of state) level COVID-19 positive cases, it clearly illustrates that emission hotspots are experiencing more numbers of COVID-19 cases (Fig. 2 (a)), which could give clear signals of certain relationships. Out of 721 districts in India, the top 142 districts (20%) are experiencing 6,279,308 positive cases (~73.4% of total COVID cases), which are exposed to ~56% of national PM$_{2.5}$ emission. When we compared the state level, we found a very good correlation coefficient of 0.66 between the state level total PM$_{2.5}$ emission load per day and state-level COVID-19 cases as compared to 0.60 in the case of district level. This value is statistically very significant and establishes that a state experiencing more air pollutants is likely to be more vulnerable to COVID-19 cases.

The pie chart in Fig. 2 (b) indicates the relative contribution of all major/minor sectors where the complete combustion-based fossil fuel is contributing near 56% and is a large source of PM$_{2.5}$. Fossil fuel-based complete combustion generates more tiny particles as
compared to traditional biofuel combustion and natural sources. Further, the emission estimation in emission inventory provides practical evidence that fossil fuel is overpowering bio-fuel (~34%) and natural source (~10%) where the contribution of fossil fuel usage in transport, power, industries, etc. in cities is as high as 63% leading to a higher rate of COVID-19 cases against cities having relatively cleaner air. To further strengthen our analysis, the air quality data is being compared with COVID-19 cases and related deaths. The spatial location of AQMS along with a value indicating the number of days in a year experiencing air quality index (AQI) between moderate to severe level along with corresponding district level COVID-19 cases (High AQI value indicates how often people are exposed to poor air quality). The estimated PM$_{2.5}$ emission load across 36 states and union territories in India is tabulated in Table 1. Until 5th November 2020, India has carried out nearly ~122 million COVID tests and found nearly ~8,553,864 positive cases which are listed in Table 1. Further, the AQI data measure during United States Environmental Protection Agency (USEPA) approved analyzers that give the number of days in a year having air quality fall between moderate to severe categories. The AQI data along with corresponding district level COVID-19 data is provided in Table 2.

Fig. 3 demonstrates the combined relation of PM$_{2.5}$ load, AQI and COVID-19 where the first initial impression suggests that AQI with high values is confined over the region with a higher number of COVID-19 cases except one or two places. When these AQI data
are correlated with the corresponding district’s COVID-19 related death cases, the correlation coefficient is found to be as high as 0.61, which is again statistically very significant, and supports our earlier claim. It is surprising to find a good correlation coefficient, which is acceptable for national scale study. The bad air quality days are having a visible relationship with the number of COVID-19 casualties. As shown in Fig. 4 (a), there’s an exponential increase in the number of casualties once the bad air quality days cross the value of 100. As bad air quality is not the only factor influencing the number of cases of COVID-19, we can see the anomaly in the increased number of casualties with the number of bad air quality days. The decrease in COVID-19 cases may be a result of strict precautions adopted by people, medicare facilities available to COVID-19 patients during the times, the severity of COVID-19 stage/string and immunity of the patient. Though Fig. 4 (b), indicating the relationship between the PM$_{2.5}$ emissions and the number of cases for COVID-19, is clear to indicate the disastrous impact of pollution on COVID-19 spread. All the cases crossing 20 k number of cases are having more than 200 Gg/yr PM$_{2.5}$ emissions or higher value. It confirms that sources of the tiny particle are fossil fuel and mostly dominated in developed and urban places. Moreover, the current findings are retrospectively more consistent with recently established studies over the Europe (Coccia, 2021; Accarino et al., 2021; Travaglio et al., 2021). The present finding establishes a strong relation between tiny particulate matter and corresponding COVID-19 cases for Indian subcontinent. If the trend of good correlation coefficient persists then communities living in states like Maharashtra, Delhi, Rajasthan, Tamil Nadu, Uttar Pradesh, Andhra Pradesh, Telangana, Gujarat, Bihar, Karnataka, Odisha and Madhya Pradesh are more likely to get affected by COVID-19 due to prolonged exposure to tiny PM$_{2.5}$.

For understanding the sector-wise contribution to total pollution load and dominance of a particular sector over the region, we have considered six main sectors: Transport, Windblown, Powerplant, Residential, Biofuel and Industry. Emissions from any other possible source are considered in a seventh section, named as “others”. We have considered seven domains over India, covering the whole country systematically for the district wise COVID-19 cases and the sector-wise pollution emission for each domain, shown in Fig. 5. The top 50 districts, which reported the highest COVID-19 infections all over India has been noted for further analysing the pollution load impact on domains.

Domain 1 covers the North Indian states Haryana, Punjab, Himachal Pradesh, Western Uttar Pradesh and the national capital Delhi. The numbers of COVID-19 cases are on the higher side in domain 1 with more districts showing severe virus infection, though, excluding Delhi, less than five districts are coming under the top 50. Domain 2 covers Bihar, Eastern Uttar Pradesh, West Bengal, parts of Jharkhand and Odisha. Though the numbers of COVID-19 infections are severe in many districts, the numbers in the top 50 districts are less than 5. Domain 3 covers Northeast India, with only one district to the top 50 COVID-19 infected districts of India. Domain 4 covers Odisha, Chhattisgarh, parts of Andhra Pradesh and Telangana. A total of 12 districts reached the top 50 COVID-19 infected district lists from this domain. Domain 5 encompasses Southern India states Tamil Nadu, Kerala and Karnataka with ten districts making it to the top 50 COVID-19 infected district lists. Domain 6 focuses on Maharashtra and parts of Telangana and has 15 districts to the top 50 districts infected by COVID-19 in India. Domain 7 is set over Gujarat, Rajasthan and parts of Madhya Pradesh and has high COVID-19 infections in many regions; however, there is no districts in the top 50 districts from this domain.

The transport sector is expected to be one of the major contributors to the total emissions, and it is the highest contributing sector in
domain 3, 5, 6 and 7; whereas it is second highest in Domain 4. The industrial sector is the highest contributing one in domain 1, and the second-highest one for domain 6. Residential emissions are the highest contributors to total PM$_{2.5}$ load for domain 2 and 4, and second-highest contributors in domain 1, 3, 5 and 7. All the other sectors (including windblown, powerplant, biofuel etc.) exists in all the domains but never received rank 1 in any of the domains created for understanding COVID-19 impact analysis. Though the transportation and industrial sectors were minimal during COVID-19 lockdown restrictions, the residential sector was untamed due to energy requirements for cooking and housing by people in the country. Except for domain 6, the residential emissions are always on rank 1 or rank 2 in all the seven representative domains chosen in Fig. 5. During the COVID-19 lockdown, the residential emissions might be considered as a key sector in associating the COVID-19 infections, associated with higher pollution load over the regions.

Fig. 5. Sector wise emissions of PM$_{2.5}$ over seven selected domains of India.
Finally, air with more PM$_{2.5}$ aggravates COVID-19 with more lethality in India in near future. Further, more advanced experimental and epidemiological studies are needed to evaluate the role of atmospheric pollution in COVID-19.

4. Conclusions

The study provides the first evidence for India about the vulnerability of people residing in highly polluted areas to COVID-19 infection with the help of the first national wide high-resolution emission inventory of tiny particle (PM$_{2.5}$), which accounts all sources of air pollutants. Present results are validated by one of the largest networks of PM$_{2.5}$ monitoring using the online USEPA approved analyzers. We can summarize the results as:

- Establishing a link between high and low emission load areas/cities with COVID-19 infections as population in a particular area is continuously living in high or low mass load regions.
- Higher numbers of COVID-19 cases are found in states like Maharashtra, Delhi, Rajasthan, Tamil Nadu, Uttar Pradesh, Andhra Pradesh, Telangana, Gujarat, Bihar, Karnataka, Odisha and Madhya Pradesh where exposure to the prolonged high concentration of PM$_{2.5}$ is relatively high.
- Major cities in the above mentioned states, e.g. Delhi, Mumbai, Chennai, Bangalore, Kolkata, Pune, Ahmedabad, Varanasi, Lucknow, Surat experienced the highest number of COVID-19 cases. The PM$_{2.5}$ emission are also higher over these areas due to fossil fuel based anthropogenic activities.
- The results demonstrated that COVID-19 and PM$_{2.5}$ emission are indicating a significant correlation (0.66) with reported cases and with resulting deaths (0.61).
- Residential burning emerged as a crucial sector in elevating/maintaining high PM$_{2.5}$ load over the country even during the lockdown situations and correlating with COVID-19 cases rise.

The present finding is crucial to frame further preparedness under the current situation to tackle the COVID-19 pandemic in densely populated countries like India. The results are helpful to slow-down the spread of the virus by providing more preventive steps and resources in areas with high pollution levels for present situation as well as for future possibilities. The compiled PM$_{2.5}$ emission inventory is an integral part of SaBe National Emission Inventory for India (SNEII v1.0) database for further air quality and climate study.

Declarition of Competing Interest

None.

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