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An application of probability density function for the analysis of PM2.5 concentration during the COVID-19 lockdown period

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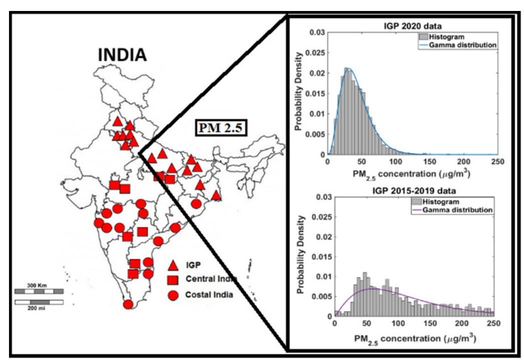
HIGHLIGHTS

- PDFs have been utilized for the investigation of PM 2.5 pollutant data of five countries.
- India has been divided into three regions (Central India, Coastal India and Indo-Gangetic Plain (IGP)) for the analysis.
- The "goodness-of-fit" of the probability density functions, to the data, was assessed, using various statistical indices.

GRAPHICAL ABSTRACT



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ABSTRACT

The first Covid-19 patient in India was reported on January 30, 2020 at the state of Kerala. The patient number rose to three by February 3, 2020. In the month of March 2020, the transmissions started to increase when the people started to return back to India from the Covid-19 affected countries. On March 12, a 76-year-old man having a travel history to Saudi Arabia was the first reported fatality in India due to Covid 19. Then for the prevention of the propagation of Covid, the Indian government declared a state of health emergency and strict counter measures were taken, including locking down of cities, prohibiting almost all avoidable activities and restricting population's mobility. From March 24, 2020 due to the complete lockdown in the country, human activities were heavily restricted in the whole geographical regions of India. This pandemic lockdown eventually serves as an opportunity to observe the background concentrations of pollutants in the atmosphere. The PM 2.5 distribution can affect human health and to overcome this problem, setting up of regulation for PM is necessary. In the present study Probability density functions (PDF) method have been utilised for the investigation of PM 2.5 pollutant data distribution of five countries namely, India, China, France, Brazil and United States of America (USA) for their respective lockdown period of 2020 and corresponding same period of 2019. A detailed study has been done for India, and for that purpose India has been divided into three regions (Central India, Coastal India and Indo-Gangetic Plain (IGP)) on the basis of different meteorological conditions. PM 2.5 concentration for hourly basis has been analysed for the lockdown period 24th March to 15th June 2020 and compared with the PM 2.5 concentration of previous year 2019 for the same time period. To understand the effect of lockdown in PM 2.5 emission in India, which will give us an idea about the background concentration, PDFs (probability density functions) have also been generated for the whole year from 2015 to 2019. The "goodness-of-fit" of the probability

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density functions, to the data, was assessed, using various statistical indices (Chi-square test). Results show that the PM 2.5 reduction during the lockdown period of 2020 as compared to the same period of 2019 is sufficiently large. This study will give a certain degree of idea to the regulatory bodies on planning and implementation of strict air quality control plans.

1. Introduction

When the concentration of particles and gases reaches to harmful levels, they act as pollutants in the air. The effects of theses pollutants can range from severe disease to temperature rise of the ambient atmosphere. Soot, mold, smoke, methane, pollen, carbon dioxide are few in many common pollutants. Air pollution is one of the alarming environmental risk, which results in early death. Each year, approximately 5 million premature deaths have been recorded due heart attacks, strokes, diabetes and respiratory diseases (Silva et al., 2016). Research suggests that long exposure to some pollutants increases the emphysema risk more than smoking a pack of cigarettes a day (Garshick, 2014). Recent studies show air pollution impacts on mental health, development, productivity and many more arena related to human society. According to World Health Organization (WHO), in 2016, the low outdoor air quality index caused around 4.2 million deaths prematurely, of which about 90% of them in developing and underdeveloped countries (Giannadaki et al., 2014). Indoor smoke, due to cooking and heating homes by burning fossil fuels, is an ongoing health threat to approximately 3 billion people. Long term exposure to air pollution increases the risk of life-threatening disease such as stroke, heart disease, cancer and the most common are respiratory disease such as Chronic Obstructive Pulmonary Disease (COPD) and asthma (Bhatnagar, 2006), while short term exposure to air pollution can cause sneezing and coughing, headaches, eye irritation and dizziness (Annesi-Maesano et al., 2012). Air quality index (AQI) is an indicator of the outdoor air pollution, which rates the air conditions across the country based on five major pollutants concentration. These major pollutants are particle pollution (or particulate matter), ground-level ozone, sulfur dioxide, carbon monoxide and nitrogen dioxide. Particulate matter (PM) consists of small airborne particles like dust, drops of liquids and soot. The source of majority of PM in urban areas is from fossil fuel burning in power plants, non-road equipment, automobiles and industrial facilities (Nagar et al., 2014). Particulate matter (PM10), smaller than 10 μm, pose higher health risks as they can be breathed deeply into the lungs and can enter into the bloodstream. Fine particles (PM2.5), particles less than 2.5 μm in diameter, can penetrate deeper into the lungs and can cause asthma, stokes, bronchitis and heart attacks (Buzea and Pacheco, 2019). In some case, PM2.5 can cause premature death due to respiratory system failure. Research show that high exposure to PM2.5 can also impair brain development in infant and children (Egondi et al., 2018).

Countries around the world are formulating various policies to find a solution to the challenges that arises due to different form of air pollution. For example, China is cancelling or partly closing coal-fired power plants in order to clean up smog-choked skies, which is caused due to years of rapid industrial expansion (Delang, 2016). California (U.S.) is leading in regulating emissions standards to improve air quality, especially in places like Los Angeles (Escobedo et al., 2008). In India, the Central Government has launched National Clean Air Programme (NCAP) under the Central Sector "Control of Pollution" Scheme as a long-term, time-bound, national level strategy to tackle the air pollution problem across the country in a comprehensive manner with targets to achieve 20% to 30% reduction in PM10 and PM2.5 concentrations by 2024 keeping 2017 as the base year for the comparison of concentration.

The Central Government of India has notified a Comprehensive Action Plan (CAP) in 2018 identifying timelines and implementing agencies for actions identified for prevention, control and mitigation of air pollution. The initiatives taken by the Government of India for the abatement and control of air pollution in Delhi and NCR since 2016 have shown good results. As per Continuous Ambient Air Quality Monitoring Stations (CAAQMS) data, the number of 'Good', 'Satisfactory', and 'Moderate' days has progressively increased to 159 in 2018, as compared to 152 in 2017 and 106 in 2016, and the number of 'Poor', 'Very Poor' and 'Severe' days has reduced to 206, compared to 213 in 2017 and 246 in 2016. In Delhi, reduction in PM2.5 levels in 2018 is 7.3% over 2017 and 14.8% over 2016. In Delhi, reduction in PM10 levels in 2018 is 8.6% over 2017 and 16.5% over 2016. Graded Response Action Plan (GRAP) was notified on January 12, 2017, for prevention, control and abatement of air pollution in Delhi and NCR. It identifies graded measures and implementing agencies for response to four AQI categories, namely, Moderate to Poor, Very Poor, Severe and Severe + or Emergency (Plan, 2018). The Ministry of Environment, Forest and Climate Change has implemented Environment Education, Awareness and Training Scheme with the objective to promote environmental awareness among all sections of the society and to mobilize people's participation for conservation of environment. Mannucci and Franchini (2017) reported that in 2015 India alone lost approximately a million human life due to ambient particulate matter (PM) pollution. Many major cities of India have ranked under 20 in the most polluted cities of the world from the past few decades due to very poor air quality (Garaga et al., 2018). Many cities never reach the air quality standard recommended by the Central Pollution Control Board (CPCB) of India and the World Health Organization (Mukherjee and Agrawal, 2018).

A number of studies have been done across the globe to observe the effect on air quality during the lockdown period of COVID-19 pandemic (Bashir et al., 2020; L. Li et al., 2020; Chauhan and Singh, 2020; Yongjian et al., 2020; Wang and Su, 2020; Sharma et al., 2020). The Government of India enforced nationwide complete lockdown on 24th March 2020 for 21 days in first phase in response to the COVID-19 pandemic, which was extended up to phase 4 and ended on 31st May 2020 (Arora et al., 2020). All type of vehicular, train and flight transportation had been banned except the essential services. This lockdown also reduced the emissions from industries substantially (Muhammad et al., 2020). Although many socio-economic consequences are developed due to the strict measures, but the air pollution levels become exceptionally minimum in India (Mahato et al., 2020). Many cities have experienced their best air quality in that period in the history of that city (Sharma et al., 2020). Hence this pandemic lockdown eventually serves as an experiment for the measurement of background concentration of pollutants of our atmosphere.

The substantial improvement in quality of air wasn't any surprise, as it was expected. What is important now is to quantify these decrements in pollution level due to the sharp reduction in the human activity and traffics in the cities, this allowed us to understand the limits of measures that should be applied for improving air quality. Low emission zone (LEZ) has a positive impact on air quality, this can be one of the several measures that should be implemented in cities to improve air quality, especially in terms of PM 2.5 (Santos et al., 2019). The lockdown situation allowed us to know the contamination levels of the outdoor air, which can be achieved by implementing this type of measure.

In the present study Probability density functions (PDF) have been utilised for the analysis of PM 2.5 distribution of five countries namely, India, China, France, Brazil and United States of America (USA) for their respective lockdown period in the year 2020 and correspondingly the same period in the year 2019. For India this analysis has been done in a very detailed manner.

In the present study PM2.5 concentration time series were statistically examined for the determination of their frequency distribution. Probability density functions (PDFs) have been utilised for the fitting of the hourly average PM 2.5 pollution data of five countries namely, India, China, France, Brazil and the United States of America (USA) for their respective lockdown period of 2020 and corresponding to the same period of 2019. PM2.5 data from a minimum of four different locations have been considered from each country. Beijing, Shanghai, Chengdu and Shenyang were considered from China; Berland, La-rochelle, Melun, Paris were considered from France; Mooca, Campinas, Santos and São José do Rio Preto were taken in account from Brazil; California, Montana, New York and Texas were considered for the collection of data from United states of America (USA). For India, the analysis has been done in a very detailed manner and hence the whole India has been divided in three parts (Central India, Coastal India and Indo-Gangetic Plane) on the basis of different meteorological conditions. The great Indo-Gangetic Plane includes different cities of Punjab, Haryana, Uttar Pradesh, Jharkhand, Bihar and West Bengal. Coastal India includes different cities of Andhra Pradesh, Tamilnadu, Kerala, Odisha and Maharastra while Central India contains the data from states of Madhya Pradesh, Karnataka and Andhra Pradesh. PM 2.5 concentration for hourly basis has been analysed for the period 24th March to 15th June 2020 for India, 24th March to 23th June 2020 for USA, 24th March to 10th May 2020 for Brazil and 14th March to 12th May 2020 for France, 1st January to 30th April 2020 for China and compared with the PM 2.5 concentration of previous year 2019 for the same period. For India, PDF's were also generated for the daily average PM 2.5 data for the whole year from 2015 to 2019. The evaluation of "goodness-of-fit" of the probability density functions, to the data was done by utilising the various statistical indices (including Chi-square and Kolmogorov-Smirnov tests). Results show that the PM 2.5 reduction is very high due to the lockdown in 2020 as compared to the same period of 2019. This study gives confidence to the pollution control regulatory authorities that a significant improvement can be achieved in air quality by strictly executing the plans for air quality control.

2. Material and methods

2.1. Data collection

Hourly average PM 2.5 concentrations data were collected from Central and state pollution control board website and analysis for various cities of India, France, China, USA and Brazil (see Fig. 1) for lockdown period of 2020 and same period of 2019. Special attention has been given to India while collecting and analysing more data over the period of 4 year (2015–2019) to gain more detail knowledge of annual trend in PM 2.5 daily mean concentration. The collected data for India is divided into three sub region IGP (Indo gangatic plain), Central India and Coastal India to identify the possibly most polluted region and difference from air quality standard (AQS).

2.2. Probability density functions (PDF)

The Lognormal, Gamma and Weibull distributions of the daily PM 2.5 concentration were calculated for the collected data discussed in the 'DATA Collection' section. All three distributions are described below in detail (Xi et al., 2013).

2.2.1. Lognormal distribution

$$P_L(X_i) = \frac{1}{X_i \ln\sigma_G (2\pi)^{0.5}} \exp\left[-\frac{(\ln X_i - \ln\mu_G)^2}{2(\ln\sigma_G)^2}\right] \tag{1}$$

In this distribution (1) μ_G is a parameter which is based on location and σ_G parameter, which is based on shape.

2.2.2. Weibull distribution

$$P_W(X_i) = \frac{\lambda}{\sigma_W}\left(\frac{X_i}{\sigma_W}\right)^{\lambda-1} \exp\left[-\left(\frac{X_i}{\sigma_W}\right)^{\lambda}\right] \tag{2}$$

In this distribution (2) λ is a parameter for shape and σ_W is a parameter for location.

2.2.3. Gamma distribution

$$P_G(X_i) = \frac{X_i^{c-1}}{d^c \gamma(c)} \exp^{-\left(\frac{X_i}{d}\right)} \tag{3}$$

In this distribution (3) d is a parameter which is based on location and c parameter which is based on shape.

In order to find out the most appropriate representative distributions of the daily PM 2.5 concentrations in the all specified location described in 'Data Collection' section, three distributions were analysed more with goodness of fit (Xi et al., 2013). The required parameters for lognormal, Gamma and Weibull distributions function were calculated based on the daily mean of PM 2.5 concentrations, which are described in the next section (Xi et al., 2013).

2.3. Calculation of parameters

If a data set is represented by a particular distribution, the exact parameters (location and shape) can be calculated from observed data. The maximum likelihood method has been deployed to calculate the parameters of the three different distributions. If the probability density function calculated from the observed data is $P(x_i)$, the probability density function of calculated distribution is $P(x_i, g_1, g_2)$ where, g_1 and g_2 are the distribution parameters, if it is true then the summation of the squares of errors (SSE) can be expressed as:

$$SSE = \sum_{i=1}^{n} (P(x_i) - P(x_i, g_1, g_2))^2 \tag{4}$$

When the $\frac{\delta \ln SSE}{\delta g_1} = 0$ and the $\frac{\delta \ln SSE}{\delta g_2} = 0$, an equation of g_1 and g_2 for maximum probability estimation can be obtained. The details of the parameters estimated with the maximum likelihood method for calculated lognormal, Weibull and Gamma distribution functions are described below.

2.3.1. Lognormal case

$$\ln\mu_G = \frac{1}{N}\sum_{i=1}^{N} \ln X_i, \qquad (\ln\sigma_G)^2 = \frac{1}{N}\sum_{i=1}^{N} (\ln X_i - \ln\mu_G)^2 \tag{5}$$

2.3.2. Weibull case

$$\lambda = \left[\left(\sum_{i=1}^{N} X_i\right)\right] \tag{6}$$

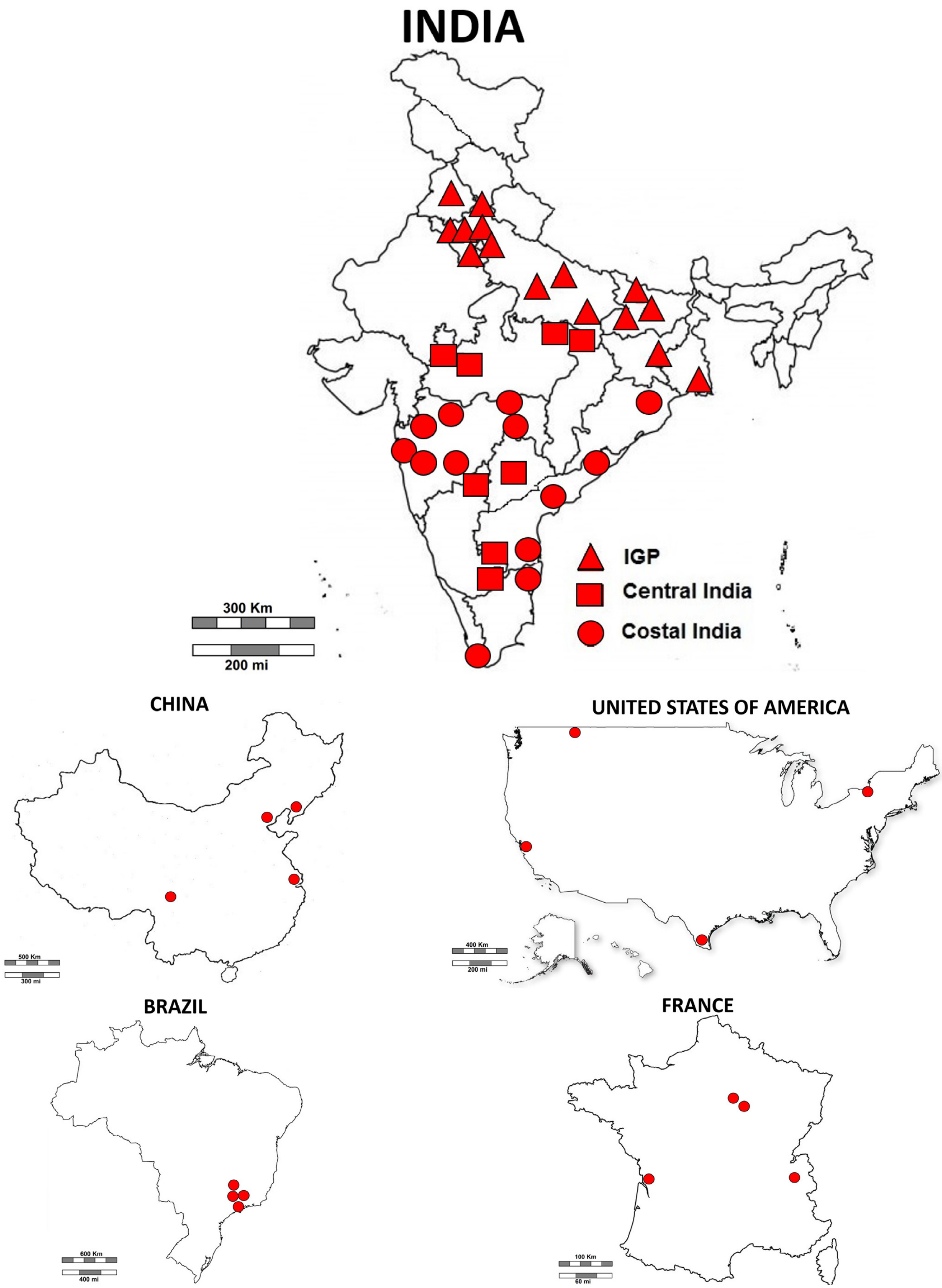

Fig. 1. Location of cities of different countries.

2.3.3. Gamma case

$$\frac{d\ln\gamma(c)}{dc} = \ln\left(\frac{c}{N}\sum_{i=1}^{N}X_i\right) - \frac{1}{N}\sum_{i=1}^{N}(\ln X_i) \qquad d = \frac{1}{Nc}\sum_{i=1}^{N}X_i \tag{7}$$

where, N is the total number of observed data for a particular location.

2.4. Goodness-of-fit

In the present work, the collected data has been fitted into statistical distribution (probability density functions). The best fit for all collected data has been presented here. The most common goodness-of-fit tests is chi-square (χ^2) test. The chi-square goodness-of-fit test can be implemented for any type of data set in which the cumulative distribution function (CDF) is calculated and then data is put into different classes. The lowest value of chi-square is an indication of best fit (Gavriil et al., 2006). It can be expressed as:

$$\chi^2 = \sum_{i=1}^{R}\frac{(O_i - F_i)^2}{F_i} \tag{8}$$

where O_i is the observed values of bin i and F_i is the simulated values of bin i. In this work, the bins were introduced for the chi-square test and can be operated through bin setting in the simulated distributions in any given data set. The bins were chosen to achieve equal probabilities for both observed frequency and expected frequency. The total number of bins was calculated automatically based on input data set. The chi-square test results of all three simulated distribution are shown in Table 1.

2.5. Pollutant emissions need to be reduced to meet the AQS

If the emission source spatial distribution has not changed, other meteorological condition and no external reaction contributing PM 2.5 concentration in the atmosphere, the emission source reduction factor ER (%) to meet the air quality standard (AQS) (Xi et al., 2013) is calculated as.

$$ER = \frac{F(C_a) - F(C_c)}{F(C_a) - C_s} \tag{9}$$

where $F(C_a)$ is the expected mean value distribution function when the extreme value equals to the AQS recommended concentration (C_a). $F(C_c)$ is the calculated mean concentration from the actual probability distribution and C_s is the background concentration in this work, which has been neglected.

For the estimation of the reduction of emission rate of a pollutant as per the above Eq. (9), we need to know which distribution is best fitted for the pollutant from chi-square test.

3. Results and discussion

The statistical distribution characteristics of hourly average PM2.5 concentration of five countries during COVID-19 lockdown period of the year 2020 and same the same period of 2019 and daily averaged PM2.5 for the period 2015–2020 for India were described using distribution functions.

The lognormal, Gamma, Weibull distributions of the PM2.5 concentration were detected for the studied time period for selected places in this study. Distributions were analysed, in order to get the best representative distributions of the PM2.5 concentrations in the five countries. Goodness-of-fit tests were performed in order to measure how good distribution fits with the input data. The most commonly used goodness-of-fit tests are Anderson-Darling (A-D) tests, Kolmogorov-Smirnov (K-S) and chi-square (Hollander and Pena, 1992). In the present study, chi-square was performed for all three examined distribution functions and the values are presented in Table 1.

The chi-square values of Gamma distribution fit were smaller than those of other distributions. The smaller values indicate a better fit with the actual data (McHugh, 2013). Considering the chi-square test results, Gamma distribution were used for the fitting of PM2.5 concentration data. Table 2 represents the mean values of PM2.5 data and the distribution parameters.

The basic statistical data of PM2.5 concentration in the four countries during their respective lockdown period in the year of 2020 and corresponding same period for the year 2019 are listed in Table 2.

During the lockdown period, the mean value of PM2.5 concentration was 40.43 μg/m^3, 29.72 μg/m^3, 13.68 μg/m^3 and 11.32 μg/m^3, respectively, in China, USA, Brazil, and France. In India, the PM2.5 values for IGP, central, and coastal regions were 42.12 μg/m^3, 30.95 μg/m^3 and 23.34 μg/m^3 respectively for the lockdown period. India and China show a significant reduction in the PM2.5 concentration during the lockdown period of 2020 with respect to the same period of 2019. From the fitted Gamma distribution function, a reduction of 32.36% is observed in PM2.5 concentration for China, 17.27% for France, 29.33% for the USA and 5.03% for Brazil during their respective lock down period. For the observation period of 24th March to 15th June i.e. the lockdown period in India, IGP region shows the highest reduction of 53.67% in PM2.5 concentration while the central and coastal regions shows a reduction of 44.44% and 43.45% respectively from the Gamma distribution fitting. Considering the daily average PM2.5 concentration of last

Table 1
Chi square test results.

Place	Year	Lognornal fit (chi-square)	Gamma fit (chi-square)	Weibull fit (chi-square)
India (IGP)	2019	57.60	46.30	50.76
India (IGP)	2020	41.70	32.21	40.75
India (IGP)	2015–2019	81.77	71.11	77.71
India (Central)	2019	77.55	59.65	65.45
India (Central)	2020	37.52	30.55	37.89
India (Central)	2015–2019	51.10	38.90	45.55
India (Coastal)	2019	28.22	29.18	29.50
India (Coastal)	2020	29.23	32.35	35.57
India (Coastal)	2015–2019	70.15	65.42	68.82
China	2019	23.26	19.19	22.54
China	2020	14.58	13.33	14.45
USA	2019	19.97	18.56	24.43
USA	2020	16.76	14.45	21.96
Brazil	2019	31.57	30.56	36.75
Brazil	2020	32.74	26.24	50.76
France	2019	12.54	11.73	12.78
France	2020	13.19	12.75	20.57

Table 2
Descriptive statistical data of hourly PM2.5 concentrations in different countries (μg/m^3).

Place	Year	Mean	Std	Gamma distribution mode	λ_g
India (IGP)	2019	87.48	65.50	68.82	2.38
India (IGP)	2020	42.12	21.96	31.88	3.19
India (IGP)	2015–2019	81.55	55.05	60.31	2.21
India (Central)	2019	42.60	26.05	37.09	2.79
India (Central)	2020	30.95	21.76	20.57	2.89
India (Central)	2015–2019	41.81	26.67	28.30	2.85
India (Coastal)	2019	39.73	22.02	28.23	3.69
India (Coastal)	2020	23.34	14.57	15.86	3.01
India (Coastal)	2015–2019	44.14	35.13	28.28	2.67
China	2019	57.71	41.60	31.08	2.86
China	2020	40.43	32.84	21.02	2.65
USA	2019	36.71	13.26	31.23	2.86
USA	2020	29.72	15.91	22.07	2.65
Brazil	2019	15.33	7.18	12.11	1.61
Brazil	2020	13.68	5.56	11.50	1.47
France	2019	14.26	8.17	9.61	1.78
France	2020	11.32	6.82	7.95	1.80

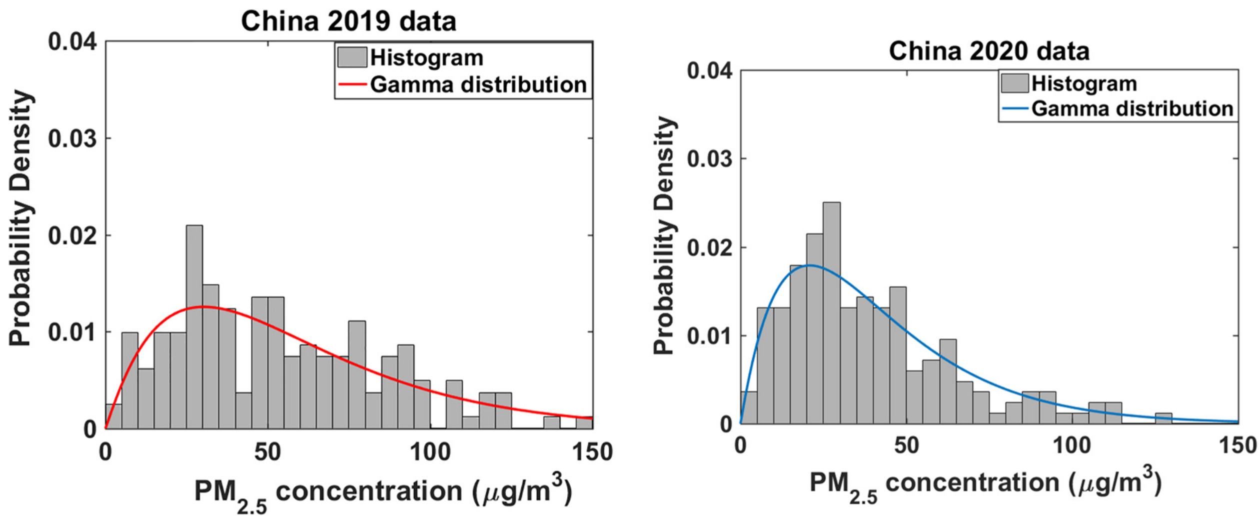

Fig. 2. PM 2.5 variation in China during lockdown period 2020 and comparison with PM 2.5 data of same period of 2019.

five year (2015–2019) this reduction was 47.13%, 27.31% 43.91% for IGP, central and coastal regions of India respectively as estimated from Gamma distribution fitting.

Figs. 2,3, 4 and 5, are showing the Gamma distribution fitting function of hourly averaged PM2.5 concentration for China, USA, Brazil and France, with their statistical distribution parameters tabulated in Table 2. The mode values of PM2.5 for lockdown period of the year 2020, for China, USA, Brazil and France were 21.02, 22.07, 11.50 and 7.95 respectively, while for the same period of year the 2019 PM2.5 mode values were 31.08, 31.23, 12.11 and 9.61 for China, USA, Brazil and France respectively. On comparison for the same period in 2019, the COVID-19 control measures in early 2020 coincide with significant reductions in PM2.5 concentrations for all considered countries. The decrement in the value of PM2.5 concentrations was also observed from the satellites data (Bauwens et al., 2020). One of the important reasons for the decreased in PM2.5 was the significant reductions of city traffic and shut down of non-essential goods industries during COVID-19 epidemic. Natural sources and the emission from stationary sources, such as steel and iron production, coal-fired power plants, pharmaceutical and food industries were responsible for the observed levels of PM2.5 concentration during the pandemic period of 2020.

The Gamma distribution fitting function of hourly averaged PM2.5 concentration for different regions of India are shown in Fig. 6. IGP shows the highest mode value of 31.88 while central and coastal India are showing mode values 20.57, 15.86 respectively for the COVID-19 pandemic lockdown period. These PM2.5 concentrations for the same period of 2019 are 68.82, 37.09, and 28.23 for IGP, central and coastal regions of India respectively.

The observed large decline in PM2.5 concentration over India is significantly very high during COVID-19 lockdown and cannot be explained by meteorology alone (Dhaka et al., 2020). The changes in meteorological parameters in 2020 are similar to the previous year 2019 as the same period (24th March to 15th June) was considered for the analysis of PM2.5 concentration. A complete lockdown was imposed by the government, and it restricted people movement, social gathering, all transport services–road, rail and air were suspended, with exceptions for essential goods transportation, police and emergency services. Industrial establishments, hospitality services and educational institutions, were also suspended (Sarkar et al., 2020). Services such as Vegetable/fruit shops, banks and ATMs, petrol pumps, other essentials and their manufacturing were exempted in all parts of India during the COVID-19 lockdown period. As an outcome of this pandemic, people movements also changed during the lockdown period (J. Li et al.,

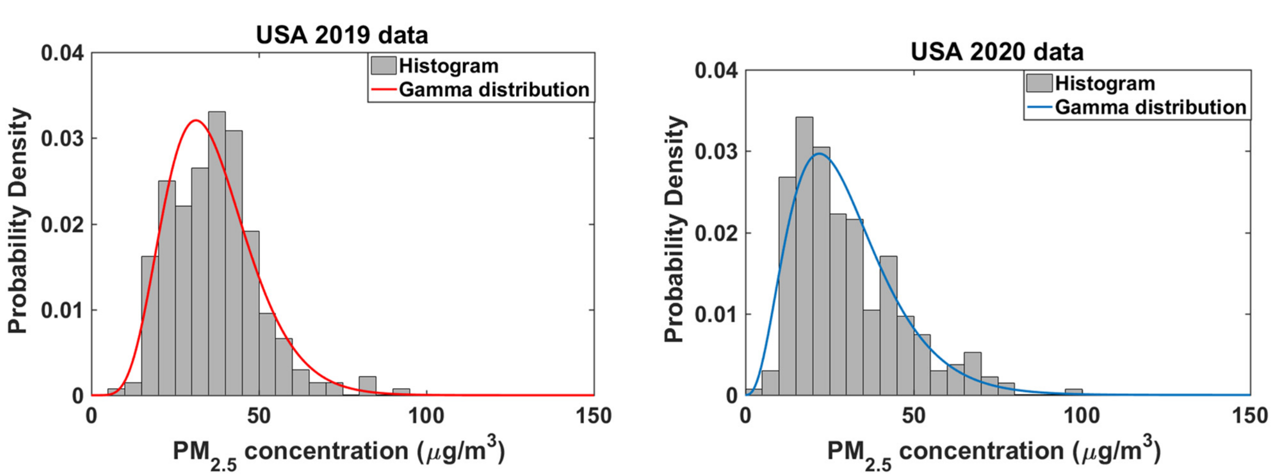

Fig. 3. PM 2.5 variation in USA during lockdown period 2020 and comparison with PM 2.5 data of same period of 2019.

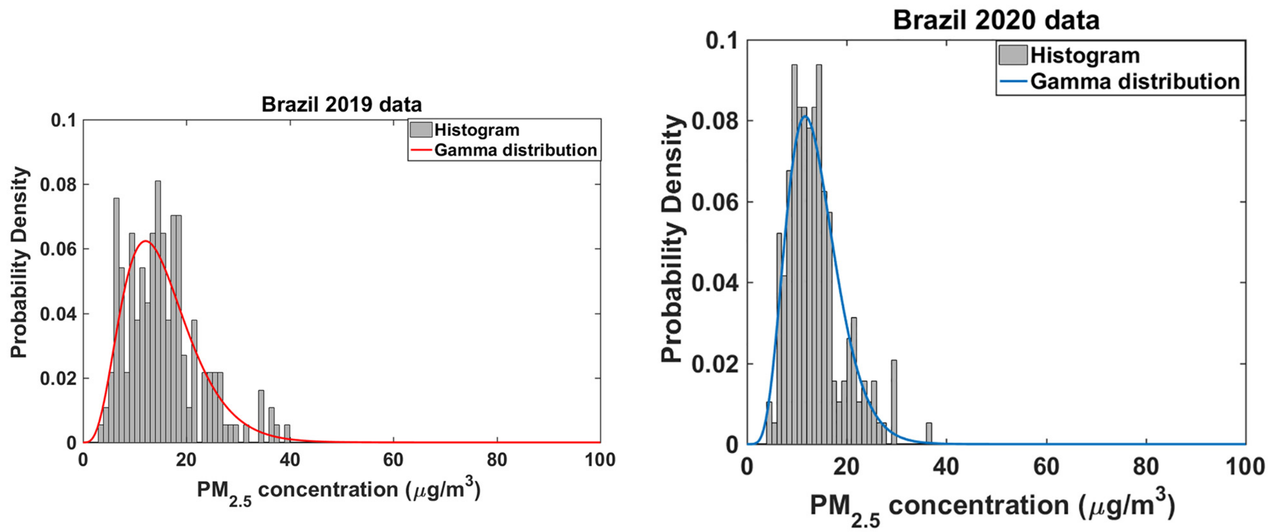

Fig. 4. PM 2.5 variation in Brazil during lockdown period 2020 and comparison with PM 2.5 data of same period of 2019.

2020). In India, during the lockdown period, parks, transit stations, workplaces, and grocery and pharmacy mobility units saw reductions of 68%, 66%, 41%, and 51%, respectively; surprisingly, residential mobility increased by 22%, as people mainly stayed at home (Saha et al., 2020) leaving their footprints on PM concentration. The highest reduction in PM2.5 concentration is observed for IGP region because this region is highly populated and is a hub for industries. Daily average PM2.5 concentrations for the studies regions in India for the last five years (2015–2019) are shown in Fig. 7. The Gamma distribution mode for the IGP region is 60.31 and for central region 28.30 and for coastal region of India it is 28.28. In general PM2.5 is much higher throughout the year in the northern part of India especially IGP (Ghosh et al., 2014). Anthropogenic activities, including industry, power generation, transportation, and residential energy usage (heating and cooking), contribute to the high concentrations of PM2.5 directly and indirectly through gas-to-particle conversions trough out the year in India (Jain et al., 2020). The average PM2.5 concentration can be brought down below the Indian National Ambient Air Quality Standards (NAAQS) by limiting household sources, all traffic movements and cutting off the industrial emissions and this pandemic has contributed a lot in achieving these ideal conditions. On comparing the reduction in PM2.5 concentration of lockdown period from the past five years daily average PM2.5 concentration, again IGP shows the highest reduction of 47.13% while central and coastal regions of India are showing a reduction of 27.31% and 43.91% respectively.

4. Conclusion

In Asia, particularly Indian subcontinent and China, PM2.5 pollutant is an important research field, and has attracted attention from all over the world. The people in this vastly populated region are exposed to extreme unhealthy air. According to research by Lim et al. (2012), India is 5th largest in ambient PM2.5 pollution concentration and China is 4th largest contributor to deaths. This research gives a good method for calculating the statistical distributions of PM2.5 concentration for multiple cities in India and others, as mentioned in detailed “Data Collection” section. This statistics could help in prediction of the exceeding percentiles. This data therefore, will contribute toward issuing useful and safety guidelines to the general public. Some important suggestions could be put forward in this work for the control of PM2.5 emissions. The 2020 lockdown brought down these activities to near zero, giving us the opportunity to accurately determine the minimum level of PM2.5 concentration. As per the findings in this

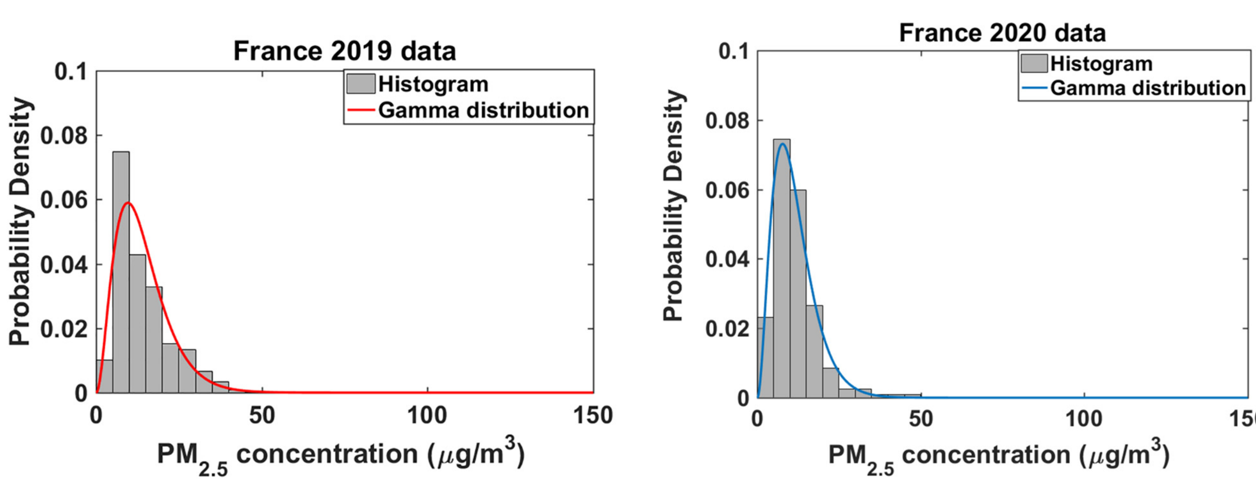

Fig. 5. PM 2.5 variation in France during lockdown period 2020 and comparison with PM 2.5 data of same period of 2019.

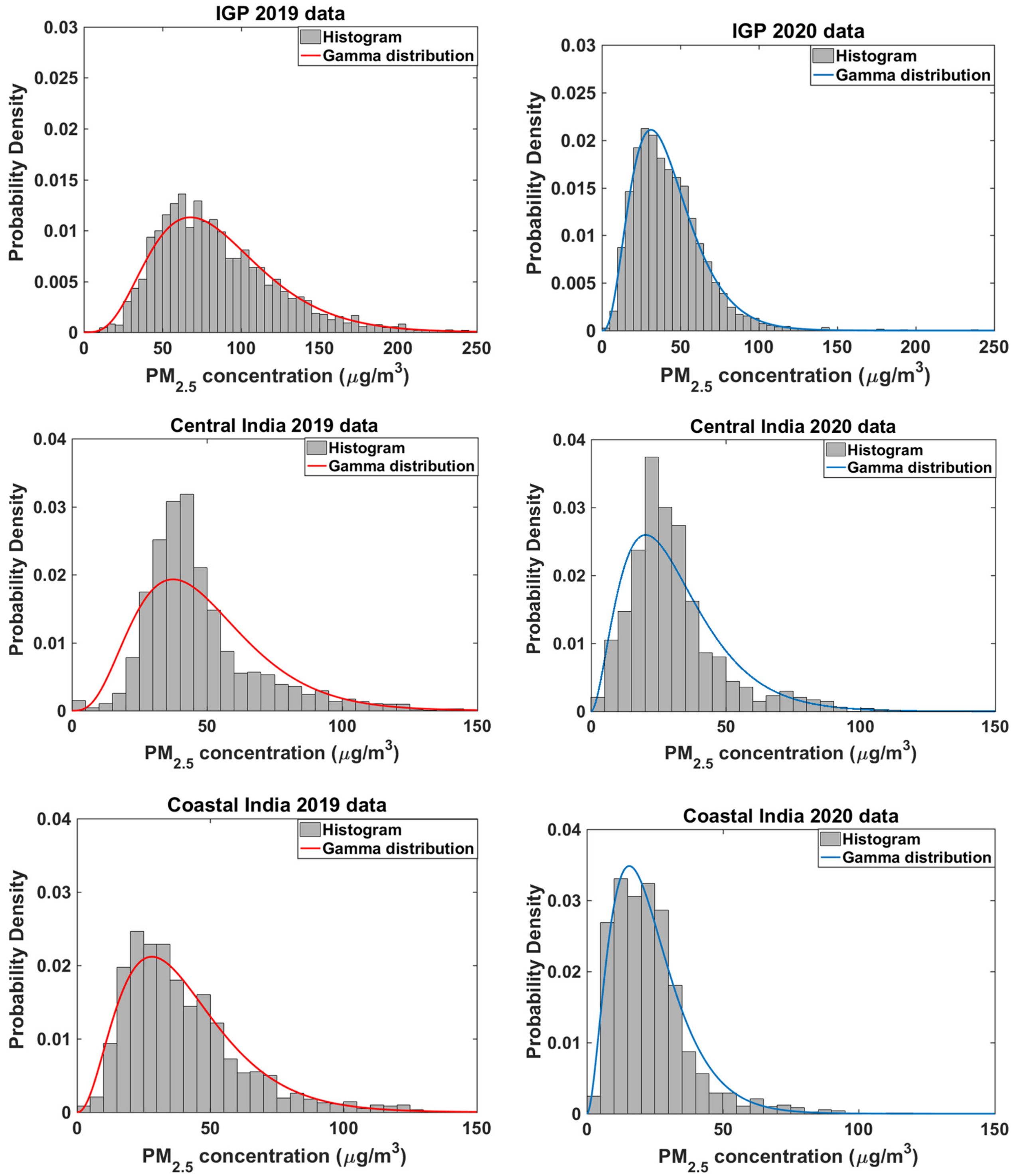

Fig. 6. PM 2.5 variation in different regions of India during lockdown period 2020 and comparison with PM 2.5 data of same period of 2019.

paper, it is suggested that the Gamma distribution can be used to strongly estimate the PM 2.5 concentration. Further, we found out that in India different cities background PM 2.5 concentration (2020 data) are almost 50% less the other year mean data. However, from other countries (France, China, USA and Brazil) data shows that 2020 lockdown is not effective in much reduction of PM 2.5 concentration as compare to India. One of the major reasons is there normal (2019 data) mean value of PM 2.5 concentration are low and close to their AQS, indication of control emission of PM 2.5 into the air. In the case of India, uncontrolled emission of PM 2.5 concentration can be easily observed, which is much needed to cut down for the better air quality. To conclude, according to the chi-square test, the Gamma distribution gives the best fit for the PM2.5 concentration, compared to all other probability functions used in this work. Therefore, the gamma distribution may be used to define the air quality standards more accurately. Further research is required to reduce the emission of PM2.5 to meet the Air quality standard and to show the statistical distribution of PM2.5 in different regions of India.

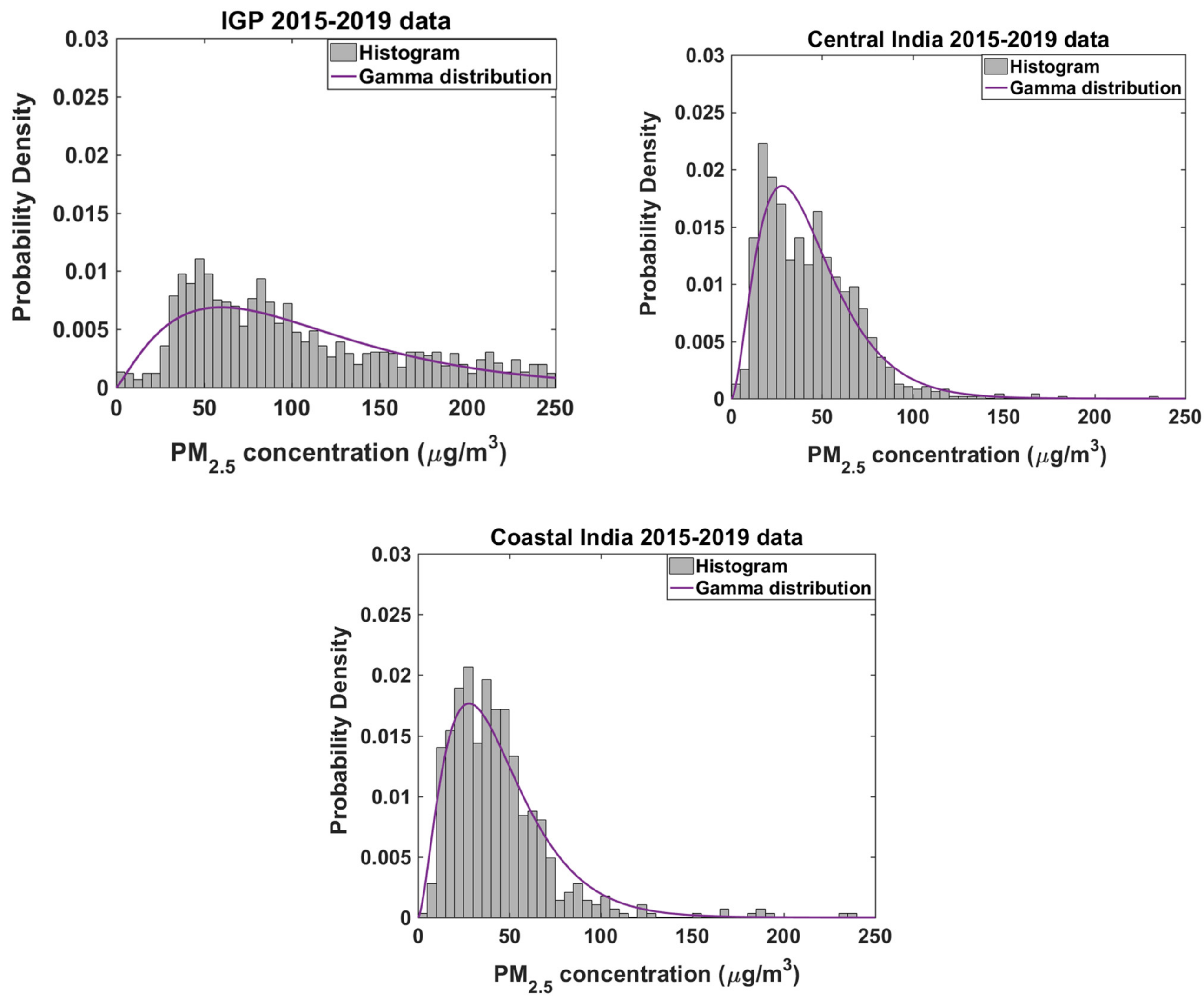

Fig. 7. PM 2.5 variation in India during the period 2015 to 2019.

CRediT authorship contribution statement

Gaurav Mishra: Conceptualization, Methodology, Formal analysis, Writing - original draft.
Kunal Ghosh: Methodology, Formal analysis, Writing - review & editing.
Anubhav Kumar Dwivedi: Data Collection, Writing - review & editing.
Manish Kumar: Data Collection, Writing - review & editing.
Sidyant Kumar: Data Collection, Writing - review & editing.
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Sachchidanand Tripathi: Conceptualization, Supervision, Writing - review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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