Statistical assessment of spatio-temporal impact of Covid-19 lockdown on air pollution using different modelling approaches in India, 2019–2020

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One of the main contributors to air pollution is particulate matter (PM_{xy}), which causes several Covid-19 related diseases such as respiratory problems and cardiovascular disorders. Therefore, the spatial and temporal trend analysis of particulate matter and the mass concentration of all aerosol particles ≤ 2.5 μm in diameter ($PM_{2.5}$) have become critical to control the risk factors of co-morbidity of a patient. Lockdown plays a significant role in reducing Covid-19 cases as well as air pollution, including particulate matter concentration. This study aims to analyse the effect of the lockdown on controlling air pollution in metropolitan cities in India through various statistical modelling approaches. Most research articles in the literature assume a linear relationship between responses and covariates and take independent and identically distributed error terms in the model, which may not be appropriate for analysing such air pollution data. In this study, a pattern analysis of $PM_{2.5}$ daily emissions in different main activity zones during 2019 and 2020 was performed. The seasonal effect was also taken into account when measuring the lockdown effect. The $PM_{2.5}$ values at the unobserved location were predicted using three popular spatial interpolation techniques: (i) inverse distance weight (IDW), (ii) ordinary kriging (OK), and (iii) random forest regression kriging (RFK), and their root mean square error (RMSE) was compared. Subsequently, the spatio-temporal intervention of lockdown on air pollution was estimated using

Statistical assessment of spatio-temporal impact of Covid-19 lockdown on
air pollution using different modelling approaches in India, 2019–2020

55

Keywords:
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inverse distance weight,
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random forest regression kriging,
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the difference-in-difference (DID) estima-tor. In winter, the transport zones, namely Anand Vihar and ITO airport, were the most affected regions. The northwestern part of Delhi is the most sensitive zone in terms of air pollution. Due to the lockdown, the weekly $PM_{2.5}$ emission decreased by 62.15%, the mass concentration of all aerosol particles ≤ 10 μm in diameter (PM_{10}) decreased by 53.14%, and the air quality index (AQI) improved by 22.40%. A proposal is made to adopt corrective measures to maintain the air pollution index, taking into account the spatial and temporal variability in the responses.

Introduction and literature review

Air pollution is the biggest threat to public health and is one of the primary causes of respiratory hazards and chronic obstructive pulmonary disease (COPD) (Hernandez–Auerbach 2012). Hence, the risk of a patient being infected by Covid-19 is high. Air pollution has life-threatening consequences on morbidity, which has been discovered by utilising the risk of morbidity due to air pollution (Ri-Map) model (Nagpure et al. 2014). In developing countries, PM_{10} is positively related to urbanisation (Fotourehchi 2016). For example, in Tehran, rapid urban expansion increases nitrogen dioxide (NO_2) emissions and other pollutant concentrations in the air, endangering human life (Ghalehteimouri et al. 2021). The Bayesian Model Averaging (BMA) provides the existence of an N-shaped pattern between national income and environmental pollution, and gross domestic product (GDP) plays a crucial role in carbon dioxide (CO_2) emissions (Mitsis 2021). It has been discerned that each year almost 0.8 million deaths and about 4.6 million people have lost their lives due to air pollution (WHO 2016). PM, the mass concentration of all aerosol particles smaller than 10 μm in diameter is effectively susceptible to penetration into the alveolar region (Harrison–Yin 2000). It is a well-established fact that PM concentrations are possibly attached to different types of life-threatening viruses and bacteria, which breaks down the human immune system entirely (Zoran et al. 2020). Thus, to alleviate pollution levels, controlling the PM concentration is an effective initial step to improve the air quality index (AQI) (Kumar et al. 2015). After the implementation of compressed natural gas (CNG) fuel, carbon monoxide (CO), and sulfur dioxide (SO_2) decreased, but there was an increase in PM_{10}, nitrogen oxide (NO_x) levels (Ravindra et al. 2006). For high traffic locations, the

level of $PM_{2.5}$ has run over the standard $PM_{2.5}$ level, especially in winter (Pant et al. 2015), and the predicted number of road vehicles will reach 25.6 million by 2030 (Kumar et al. 2011). Some studies found that pollution affects children because of their weak immunity system (Schwartz 2004) and increases the risk of gestational diabetes mellitus (GDM) in pregnant women (Robledo et al. 2015). Pollution at an alarming level attracts researchers' recognition so much so that the influence of different policies, for example, odd and even trials, are reviewed in detail, and are considered effective in mitigating pollution during the early morning and late evening hours (Kumar et al. 2017).

From previous studies, we are aware of the deadlier impacts of air pollution and the necessary measurements to control these pollutant concentrations in the air. However, to mitigate pollution, different policies will be effective when we predict the trend of pollutant concentrations in the air with better accuracy. Only then can proper measures be taken to control this pollution. Therefore, a review of the previously used methodologies is very important. SO_2 and total suspended particles (TSP) were effectively correlated with temperature, wind speed, atmospheric pressure, and relative humidity during the winter season from 1999 to 2005 (Ilten– Selici 2008). In Turkey, the AQI was improved by banning use of hard coal of poor quality for domestic purposes, and the SO_2 and TSP concentrations decreased in the air with increasing temperature, pressure, and wind speed. Time series forecasting and data mining techniques have been implemented to show the patterns of several pollutant concentrations (Sharma et al. 2018). In that study, it was indicated that in the future, a heavy load in transportation would be a key factor contributing to significant NO_x emissions and crop burning, and construction work would be mainly responsible for high concentrations of PM_{10} and $PM_{2.5}$ concentration in the air. An exhaustive statistical analysis of pollution data is also available; for example, seasonal influence in daily time data, at what time the pollution is at its peak, is justified statistically (San Martini et al. 2015). In that study, it was detected that in Beijing, the pollution is minimum in spring, and in the remaining cities, the pollution is minimum during the summer. The pollutant concentration is at its peak in Beijing during the night, whereas in the remaining cities, the pollution is generally maximum during rush hours in the morning (San Martini et al. 2015). Combining geospatial interpolation methods with ML models, researchers have effectively predicted mud content in the southwest part of Australia. For this purpose, they used RFK and random forest inverse distance square (RFIDS), and detected that these hybrid models are capable of interpolating the measurement of accuracy because they reduce RMSE by 30% and 19%, respectively (Li et al. 2011). Researchers have combined bidirectional long short-term memory (BLSTM) networks with IDW to exhibit a new methodology, that is, IDW-BLSTM. This helps analyse the long-term temporal upshot of pollution (Ma et al. 2019). Many researchers have attempted to develop new models for acquiring authenticity. There

Statistical assessment of spatio-temporal impact of Covid-19 lockdown on
air pollution using different modelling approaches in India, 2019–2020

57

are three main types of accessible models: (i) deterministic models, for example, the operational street pollution model (OSPM) (Berkowicz 2000), (ii) statistical models, namely the multiple regression model (MLR) (Berkowicz 2000), and (iii) machine learning models, such as random forest (RF) (Hengl et al. 2007). In Table 1 there is a precise and foremost recapitulation of previous research works regarding the methodologies used in the previous case study.

Table 1

Important methodologies in previous research work

Location	Focus area	Prime detection	Reference
Delhi	Estimation of $PM_{2.5}$	IDW and OK	Shukla et al. 2020
Guangdong province, China	Spatio-temporal estimation of $PM_{2.5}$	IDW-BLSTM performed efficiently	Ma et al. 2019
China	Spatio-temporal estimation of $PM_{2.5}$	RFSTK responded satisfactorily	Shao et al. 2020
China	Spatial and temporal pattern recognition of $PM_{2.5}$ concentration	Linear regression and grey system correlation analysis	Lu et al. 2017
Delhi	Relationship between $PM_{2.5}$ and other spatio-temporal covariates are explained	Six ML learners	Mandal et al. 2020
China	Statistical analysis of $PM_{2.5}$ concentration	Seasonal influence	San Martini et al. 2015

In the year, 2020 the situation was different from that in previous years. The Covid-19 pandemic, caused many countries to institute social lockdown measures to break the chain of this virus. In India, the central government announced a lockdown with the same intention. The social and transportation movement was fully restricted, except in some emergencies because of the „Janata Curfew" announced by the honourable Indian Prime Minister. After announcing the lockdown, it was observed that the pollution declined on a large scale. Many researchers have detected a relationship between Covid-19 and air pollution. They proposed lockdown as a measure of controlling pollutant emissions because air pollution significantly contributes to weakening the human immune system, causes respiratory hazards, and creates a greenhouse effect. The use of interrupted time series modelling to test the significant influence of lockdown in changing the pollutant concentration has been discussed (Cameletti 2020). The lockdown intervention reduced nitrogen-di-oxide (NO_2) and PM_{10} concentration in the city of Brescia significantly (Cameletti 2020). In Wuhan, a drastically decreasing tendency is noticed in pollutant concentrations, particularly NO_2 and SO_2. Just prior to the lockdown, the NO_2 concentration was 23.1–40.7 µg/m³, whereas after lockdown, that concentration varied between 13.8–28.6 µg/m³ due to the strict restriction of transportation movement (Brimblecombe–Lai 2020). Bashir et al. (2020) found that average temperature, minimum temperature, and air quality are linearly related to

the Covid-19 lockdown. It has stopped the spread of the Covid-19 virus in New York, USA, and has improved air quality. The improved air quality indicates that green environmental policies should be promoted because they mitigate the spread of infectious diseases, such as Covid-19. Shrestha et al. (2020) observed a significant decline in $PM_{2.5}$, PM_{10}, and NO_2 concentrations in cities such as Bangalore, Beijing, Bern, Delhi, Lima, London, Madrid, New York, Paris, Seoul, Sydney, Tokyo, Ulaanbaatar, and Vienna. The National Air Quality Index (NAQI) was notably improved during the lockdown (DL) period in megacity Delhi, and the average PM_{10} and $PM_{2.5}$ concentrations in the air decreased by 57 and 33%, respectively, on average, compared to the previous three years (Mahato et al. 2020). Moreover, after the commencement of the first day of lockdown, the air quality improved by 40%, and approximately 54, 49, 43, 37%, and 31% decline in AQI was seen in the central, eastern, southern, western, and northern regions of NCT Delhi, respectively (Mahato et al. 2020). $PM_{2.5}$ saw the largest reduction among the other important pollutant concentrations in most of the cities in India, and AQI was lower compared to the previous years in India (Sharma et al. 2020). The AQI improved by approximately 30–46.67%, and there was a huge reduction in the PM concentration level in Delhi, followed by UP and Haryana, because of fewer vehicles on the road and reduced industrial emissions (Gautam et al. 2021). The researchers evaluated spatio-temporal variations of pollutants in Delhi, Mumbai, Chennai, Bangalore, and Kolkata over four time periods: March 2019–April 2019 and the same period in 2020. The other time points were 10th March 2020 to 20th March 2020, considered as before lockdown (BL) and 25th March 2020 to 6th April 2020 (DL), which highlighted a statistically significant decline in all the pollutants (Jain–Sharma 2020).

Although the proposed temporal trend and spatial interpolation models performed well, they had some limitations. Previous research has ignored whether the relative temporal change of pollutant concentrations in the air of a particular time window depends only on the window size or time point. If it depends on time, it is obvious that seasonal influence and secular trend will exist. If it is independent of time, measuring the seasonal effect of pollutant concentration does not make any sense. In addition, when researchers analyse the trend of pollutant levels in the air, they neglect to explain the pollutant concentration trend. Let us assume that in winter, the trend of $PM_{2.5}$ is increasing (Mahato et al. 2020), but the question is whether crop burning during winter is the sole cause of this trend, or there are some other issues which are also responsible for this trend. Likewise, before applying the spatial interpolation model, there is no information to validate whether the covariates vary spatially, because if the datasets are not spatially correlated, then it is easy to interpret that the monitoring stations are located far from each other. As a result, we miss the spatial information contained in the neighbourhood of each monitoring station. Similarly, when they measured the spatio-temporal impact of lockdown, they compared the averages of pollutant concentrations and concluded about the spatio-temporal effect of lockdown. However, when comparing the

**Statistical assessment of spatio-temporal impact of Covid-19 lockdown on
air pollution using different modelling approaches in India, 2019–2020**

59

averages of the pollutant concentrations, they include the intervention of lockdown and seasonal land use information simultaneously, which is an ambiguous measurement. Limited information is available regarding the frequency distribution of pollutants. As a result, the probabilistic distributions are fully ignored in the context of air pollution in Delhi, and the statistical discussion of the effectiveness of the major activities and lockdown in $PM_{2.5}$ emission is omitted. In addition, at the time of fitting the variogram models, there was no concrete discussion of Delhi air pollution.

Therefore, to mitigate the above shortcomings, we first discuss the features of the frequency curves of daily $PM_{2.5}$ emission. Thereafter, we discuss the effectiveness of lockdown and the importance of major activity at $PM_{2.5}$ level with statistical logic (Figure 1).

Figure 1

Detail of the research work
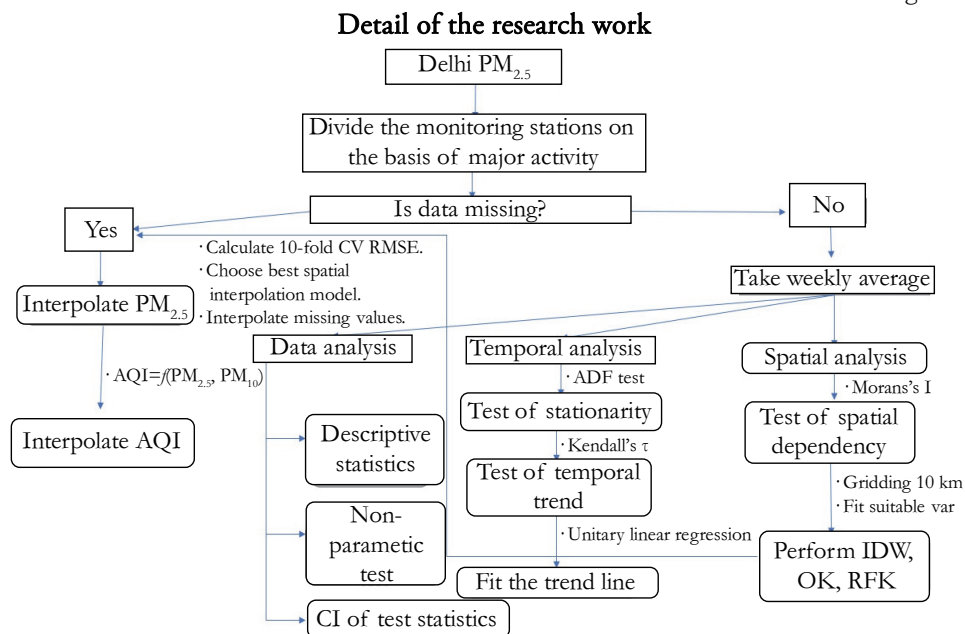
Before conducting the temporal trend analysis, we checked the stationarity of the time-series data. We then studied the temporal trend and seasonal influence of the dataset. We discussed the data for which weeks are spatially correlated using Moran's I index. Subsequently, we interpolated the $PM_{2.5}$ value of unobserved locations using three popular spatial interpolation techniques, IDW, OK, and RFK, using 10 km×10 km spatial resolution, and compared them based on the RMSE. We estimated the lock-down effect in major activity zones using the (DID) estimator. Thereafter, we emphasise the spatio-temporal behaviour of each monitoring station for each season.

Data and methodologies

Study area and site selection

Here, we selected Delhi, the capital of India, to study the air pollution of BL and DL during the first wave of the Covid-19 pandemic in India. Being the capital of India, rapid urbanisation, increasing amounts of traffic, increasing population, and energy consumption at an alarming level are mainly responsible for air pollution in Delhi. Sometimes, the $PM_{2.5}$ concentration in the air reaches 999 µg/m³ (Mukherjee et al. 2018). A spike in the vehicle count in Delhi has been identified as the cause of higher pollutant concentrations in the air (Samal et al. 2013). Among all air pollutants, $PM_{2.5}$ especially affects public health (Zheng et al. 2015).

We considered the air pollution data collected by the monitoring stations, maintained by the Central Pollution Control Board (CPCB), Delhi Pollution Control Committee (DPCC), and the Indian Institute of Tropical Meteorology (IITM). For our research purpose, we collected data on several air pollutants, such as $PM_{2.5}$, PM_{10}, CO, and NO, from the CPCB websites. To map the spatio-temporal distribution of air quality in Delhi and to contrast between the $PM_{2.5}$ concentrations of the BL and DL periods, these data play a key role. In this dataset, there are 38 monitoring stations, which are displayed in Figure 2, where the data were collected over 24 hours.

Figure 2

List of monitoring stations in Delhi

• CPCB monitoring stations
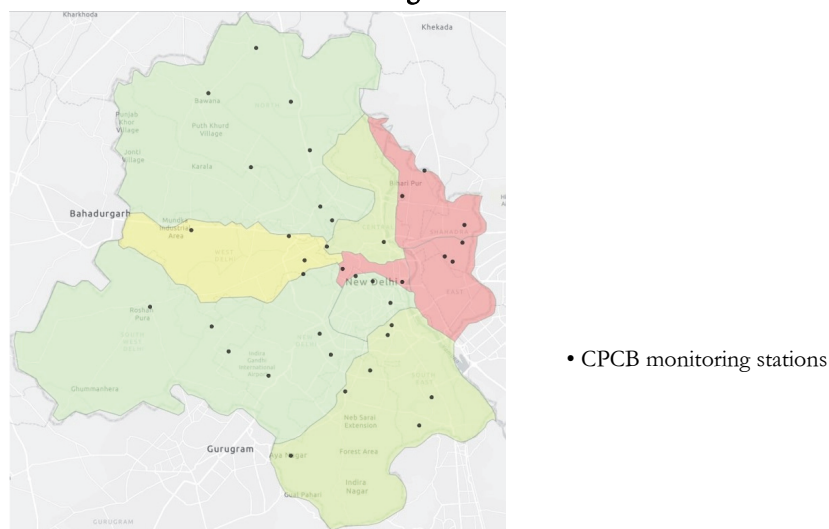
In this study, the time period was taken from 1st January 2019 to 28th February 2021 as a result of which the spatio-temporal impact of lockdown on $PM_{2.5}$ is visible. However, there are two shortcomings in applying spatial interpolation

Statistical assessment of spatio-temporal impact of Covid-19 lockdown on
air pollution using different modelling approaches in India, 2019–2020

61

techniques to estimate $PM_{2.5}$ in Delhi NCR because of the unavailability of data and the distance between Delhi, NCR, and other monitoring stations. Among the 38 monitoring stations, there is no data available for $PM_{2.5}$ in East Arjun Nagar, Delhi, and the data for the remaining stations are sometimes missing, such as in Anand Vihar from 4th April 2020 to 18th April 2020 and from 1st May 2020 to 14th May 2020 in DTU, the data are missing from 3rd February 2019 to 6th February 2019 and from 28th March 2020 to 31st March 2020. Based on the spatial analysis, some of the stations are divided based on major acts, namely, transport, residential, commercial, and institutional zones, as shown in Table 2.

Table 2

Major activity of monitoring stations

S.No.	Monitoring station	Major activity
1	AnandVihar	Transport
2	IGI Airport, T3	Transport
3	ITO, Delhi	Transport
4	R K Puram	Residential
5	Punjabi Bagh	Residential
6	Ayanagr	Residential
7	Burari Crossing	Residential
8	Sirifort	Residential
9	Mandirmarg	Commercial
10	Lodhi Road	Commercial
11	Shadipur	Commercial
12	CRRI, Mathura Road	Institutional
13	DTU	Institutional
14	NSIT, Dwaraka	Institutional
15	North Campus DU	Institutional
16	Pusa	Institutional

Spatio-temporal methods

In this study, we examine the characteristics of $PM_{2.5}$ emission in the air, and we measure the statistical significance of lockdown on air pollution. In this section, we present a brief overview of the statistical methods for spatial, temporal, and spatio-temporal impact analyses.

Let y_{ts} be the observed value of the dependent variable at the tth time point at the sth location, where $t=1,2,3,\ldots,n$ and $s=1,2,3,\ldots,d$. Likewise, $x_{ts}^{(i)}$ be the observed value of the tth independent variable at the tth time point on s^{th} location. We also studied the stationarity of the data. If the ACF of the data converges to 0, then the data are strictly stationary; otherwise, they are non-stationary (Brockwell 2002). If the data are non-stationary, then trends, seasonality, cyclical fluctuations, and randomness exist in the data. Let us assume that the

temporal cross-section of the dataset is additive in time, and the additive time series model is

$$y_{ts} = T_{ts} + S_{ts} + C_{ts} + R_{ts} \tag{1}$$

In equation (1),

T_{ts} = Measurement of the secular trend at s^{th} location at t^{th} time point.

S_{ts} = Measurement of seasonality at s^{th} location at t^{th} time point.

C_{ts} = Measurement of cyclical fluctuation at s^{th} location at t^{th} time point.

R_{ts} = Measurement of irregularity at s^{th} location at t^{th} time point.

Then, we measured the seasonal influence of tth time point on the y_{ts} using the ratio-to-moving average method. We analysed the temporal trend of the y_{ts} for t^{th} time point for every geographical location during the two years.

After analysing the temporal behaviour, we focused on the spatial trend of y_{ts}. In this situation, we perform the test of spatial auto-correlation using Moran's I index at 0.05 level of significance (Till et al. 2018) where

- H_0: The data are not spatially autocorrelated ($I=0$).
- H_1: The data are spatially autocorrelated ($I \neq 0$).

If the data are spatially auto-correlated, then we perform a spatial trend analysis of the y_{ts}. In this scenario, the main challenges are: (1) The unobserved gridded data points (10 km × 10 km) and (2) The missing values. Therefore, we first concentrated on the spatial interpolation. For this purpose, we used three well-known geospatial interpolation techniques and compared their interpolation accuracies. These three spatial interpolation methods are (i) IDW, (ii) OK, and (iii) RFK. In IDW (Wackernagel 2003), the interpolated y_{ti}^* is the unobserved y_{ts} where $s = i$. This is the unobserved value at the ith location at the tth time point. The IDW equation can then be expressed as follows:

$$y_{ti}^* = \frac{\sum_{s \in N(i)} w_s^{IDW} y_{ts}}{\sum_{s \in N(i)} w_s^{IDW}} \tag{2}$$

In equation (2), $N(i)$ is the neighbourhood point of the ith location, and $w_s^{IDW} = \frac{1}{d(s,i)^p}$; $s \neq i$ and $s \in N(i)$. In equation (2) the performance of IDW is dependent on the choice of p. Similarly, in OK, (Cressie 2015) the equation can be written as:

$$y_{ti}^* = \sum_{s=1}^{d} w_s^{OK} y_{ts} \tag{3}$$

In equation (3), w_s^{OK} is calculated using the variance-covariance function fitting an appropriate variogram with better accuracy, and this variogram is chosen based on the minimum RMSE. These two methods might look identical, but by their origin, they are completely different, as IDW is purely the deterministic approach, whereas OK is purely the probabilistic approach. Now we think about a new hybrid

Statistical assessment of spatio-temporal impact of Covid-19 lockdown on
air pollution using different modelling approaches in India, 2019–2020

63

geospatial interpolation technique that is efficient enough regarding the sense of interpolation, that is, RFK.

RFK combines two methods: (*i*) RF to fit the explanatory variables, and (*ii*) OK to fit the OOB errors with expectation 0 (Hengl et al. 2007). Let $\vec{x}_0$ be the unobserved location and $\vec{x}_i$ be the ith neighbourhood location of $\vec{x}_0$ where $i = 1,2,\ldots,n$ then the RFK (Shao et al. 2020) model is :

$$y_{ti}^* = \sum_{s \in N(i)} \sum_{j=1}^{m} \alpha_j x_{ts}^{(j)} + \sum_{s \in N(i)} w_s^{RFK} \epsilon_{ts} \tag{4}$$

where, α_j is the RF regression coefficient, w_s^{RFK} is the kriging weights and ϵ_{ts} are the OOB errors of the sth location. Using the bootstrapped sample, RF performs regression between the explanatory variables by building a huge collection of trees randomly which do not correlate (Breiman 2001). It provides important measures such as the Gini-Mean decrease (G) (Grömping 2009), and error rate. Thereafter, we considered the spatial features of the OOB error and interpolated the OOB errors using the OK. The RF model is fitted on the data in R using the „randomForest" package (RColorBrewer 2018). In this function, there are two important parameters: ntree and mtry, where ntree denotes number of uncorrelated decision trees and mtry denotes number of the independent splitting variables. The explanatory variables are listed in the following Table 3.

Table 3

List of variables used in RFK model and their corresponding measuring units

Symbol	Variable details	Unit
NO	Nitric oxide	$\mu g/m^3$
NO_2	Nitrogen di-Oxide	$\mu g/m^3$
NO_x	Other nitrogen oxides	$\mu g/m^3$
CO	Carbon mono oxide	$\mu g/m^3$
PM_{10}	Particulate matters with a diameter of 10 micrometers	$\mu g/m^3$
$PM_{2.5}$	Particulate matters with a diameter of 2.5 micrometers	$\mu g/m^3$
East	Easting position longitude	$/°N$
North	Northing position latitude	$/°E$

We now consider the spatio-temporal intervention of lockdown on $PM_{2.5}$ emission. Therefore, we used the DID regression (Mascha–Sessler 2019) technique to estimate the treatment effect by comparing the differences in the outcomes of the pre-and post-intervention periods and the outcomes between the intervention and control groups (in this case, the treatment group was lockdown and the control group was the major activity zone). DID regression can be expressed as follows:

$$E(y_{ts}|Z_s, I_t) = \beta_0 + \beta_1 \cdot I_t + \beta_2 \cdot Z_s + \beta_3(I_t \cdot Z_s) + \epsilon_{ts} \tag{5}$$

In the above equation (5), Z_s is the control group, I_t is the indicator variable which is equal to 1 if the treatment group is present and 0 if the treatment group is

absent, $\beta_i; i = 0,1,2,3$ are the linear regression coefficients and ϵ_{ts} are the residuals of this linear model. $E(y_{ts}|Z_s, I_t)$ is the conditional expectation of y_{ts} given Z_s and I_t which measures the conditional average of y_{ts} in the presence of Z_s, I_t. In equation (5), β_3 measures the interaction effect of Z_s and I_t on y_{ts}. In this study, β_3 estimates the spatio-temporal effect of the lockdown of $PM_{2.5}$ in the major activity zones.

Model accuracy

The accuracy of the models are validated by the following three methods :
  1. R^2 that is, the coefficient of determination,
  2. RMSE,
  3. K-fold CV.
Suppose that y_{ts}, $\hat{y}_{ts}$ and $\bar{y}$ are the observed and predicted values of the variable at the tth time point on the sth location and the mean of the values of the variable, respectively. The data are available for d locations and n time points. Then, the sum of squares of errors (SSE), mean square error (MSE), and total sum of squares (TSS) are defined as follows:

$$SSE = \sum_{t=1}^{n} \sum_{s=1}^{d} (y_{ts} - \hat{y}_{ts})^2 \tag{6}$$

$$MSE = \frac{\sum_{t=1}^{n} \sum_{s=1}^{d} (y_{ts} - \hat{y}_{ts})^2}{nd} \tag{7}$$

$$TSS = \sum_{t=1}^{n} \sum_{s=1}^{d} (y_{ts} - \bar{y})^2 \tag{8}$$

Then, using equation (6), (8), and (7), the measurements of accuracy are respectively $R^2 = 1 - \frac{SSE}{TSS}$ and RMSE $= \sqrt{MSE}$, where R^2 denotes what proportion of $PM_{2.5}$ is explained by the model, and in contrast, RMSE denotes the unexplained variability. Here, to find the value of p in IDW, R^2 and RMSE play a prime role (minimum RMSE and maximum R^2) and to validate the K-fold CV, K was taken as 10. The 10-fold CV indicates that the dataset is divided into 10 data sets at random, and among these datasets, 9 data sets were taken as the training dataset, and 1 data set was taken as a test dataset. Likewise, to apply the variogram model, we have determined salient parameters such as range, nugget, and sill aiming towards the minimum RMSE. To uphold the OK predicted result, we brought about a 10-fold CV. In RFK, after interpolating the OOB residuals, the final predicted value was ratified by the RMSE.

Statistical assessment of spatio-temporal impact of Covid-19 lockdown on
air pollution using different modelling approaches in India, 2019–2020
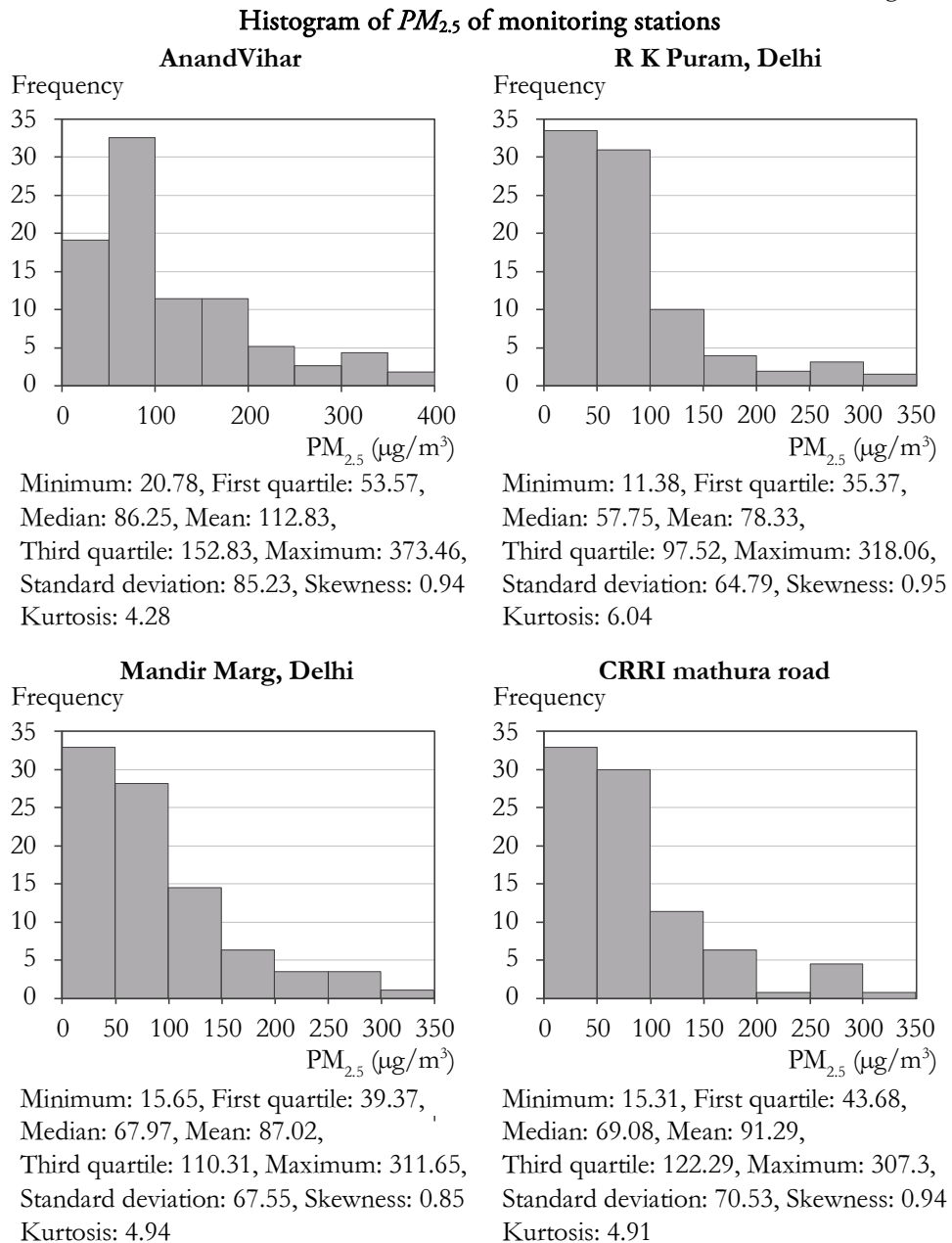
65

Result and discussion

Descriptive studies

This study included 25,875 data points in this research work. We have noticed a descriptive summary of the data in Table (4) in a nutshell. During the entire period, the minimum and maximum values of $PM_{2.5}$ during the entire period of time are respectively 10.22 μg/m³ and 715.04 μg/m³. As a result, we can understand that there exists a huge variation in 24 hour $PM_{2.5}$ values in the air of Delhi. To capture the entire dispersion of the data, we studied the standard deviation of $PM_{2.5}$, which was 75.18 μg/m³. In the entire data set, the first 25 percentile of daily $PM_{2.5}$ data are lying under 41.88 μg/m³, the 50 percentile of daily $PM_{2.5}$ data are under 67.77 μg/m³, and the 75 percentile of daily $PM_{2.5}$ data are under 122.14 μg/m³. In addition, the mean and mode of the daily $PM_{2.5}$ data are respectively 94.12 μg/m³ and 45.044 μg/m³ (from Table (4). For the entire dataset, the mean was greater than the median, and the median was greater than the mode. Pearson's first measure of skewness is 0.6527736, which indicates that the frequency curve of $PM_{2.5}$ is positively skewed, which is the degree of departure from the symmetry. Therefore, the frequency curve had a higher density in the smaller values of 24-hour $PM_{2.5}$ emission data than the larger values of 24-hour $PM_{2.5}$ emission data, and after the mode of the data, the density of the frequency curve decreased with increasing values of $PM_{2.5}$. The kurtosis of $PM_{2.5}$ is 2.211476, which is greater than 0. Therefore, the distribution of $PM_{2.5}$ is leptokurtic, indicating that there is a high density in the neighbourhood of the daily $PM_{2.5}$ data (i.e. 45.044 μg/m³ from Table 4).

Table 4

Descriptive statistical measurements of 24 hour
$PM_{2.5}$ emissions during the entire time period

Summary	Value, (μg/m³)
Minimum	10.22
First quartile (Q_1)	41.88
Median (Q_2)	67.77
Mean	94.12
Third quartile (Q_3)	122.14
Maximum	715.04
Mode	45.044
Standard deviation	75.18

Figure 3

Histogram of $PM_{2.5}$ of monitoring stations

AnandVihar

Minimum: 20.78, First quartile: 53.57,
Median: 86.25, Mean: 112.83,
Third quartile: 152.83, Maximum: 373.46,
Standard deviation: 85.23, Skewness: 0.94
Kurtosis: 4.28

R K Puram, Delhi

Minimum: 11.38, First quartile: 35.37,
Median: 57.75, Mean: 78.33,
Third quartile: 97.52, Maximum: 318.06,
Standard deviation: 64.79, Skewness: 0.95
Kurtosis: 6.04

Mandir Marg, Delhi

Minimum: 15.65, First quartile: 39.37,
Median: 67.97, Mean: 87.02,
Third quartile: 110.31, Maximum: 311.65,
Standard deviation: 67.55, Skewness: 0.85
Kurtosis: 4.94

CRRI mathura road

Minimum: 15.31, First quartile: 43.68,
Median: 69.08, Mean: 91.29,
Third quartile: 122.29, Maximum: 307.3,
Standard deviation: 70.53, Skewness: 0.94
Kurtosis: 4.91

Statistical assessment of spatio-temporal impact of Covid-19 lockdown on air pollution using different modelling approaches in India, 2019–2020

67

For better visualisation and proper understanding, the purpose histogram of $PM_{2.5}$ of the four major monitoring stations is shown in Figure 3, which is sufficient to show that the graph is positively skewed. In this Figure 3, we just show the pattern of the data of some sample monitoring stations to get a brief idea about the pattern of daily $PM_{2.5}$ emissions in each monitoring station. In this figure, we plotted the basic histogram of Anand Vihar, R K Puram, Mandir Marg, and CRRI Mathura. In this Figure 3, we find that the minimum daily $PM_{2.5}$ emission is being detected in R K Puram (i.e. 11.38 μg/m³), and maximum daily $PM_{2.5}$ emission is being identified in Anand Vihar (i.e. 373.46 μg/m³). In Anand Vihar, the maximum variation is detected because Anand Vihar is one of the paramount transport zones (Figure 3) with heavy flow of vehicles and the daily $PM_{2.5}$ concentration in the air is very high. Similarly, because of the Covid-19 lockdown, transportation was restricted; as a result, there was a massive decline in 24 hour $PM_{2.5}$ emission. Therefore, owing to the large variation, the standard deviation was significant for Anand Vihar.

The CI of mean $PM_{2.5}$ during the cumulative time span was 91.37–96.87 at a confidence level of 0.95. Thus, it can be concluded that people are at a high risk of exposure to unhealthy air. In this study, we divided the entire time period into the following three parts in Table 5.

Table 5

Division of entire time periods

Time period	Starting date	Starting week	Ending date	Ending week
Before lockdown (BL)	17-03-2019	12	29-06-2019	26
During lockdown (DL)	22-03-2020	12	27-06-2020	26
After lockdown (AL)	28-06-2020	27	29-08-2020	36

Then, we calculated the weekly average of $PM_{2.5}$ for each week and compared the weekly averages of $PM_{2.5}$ values. The CI of the mean difference of BL, DL; BL, AL; and DL, AL are respectively 22.86–28.16, 44.68–49.87, and 19.57–23.96 at a significance level of 0.05. This result is very useful for distinguishing the pattern of $PM_{2.5}$ emissions during the three time periods. This study leads us to one of the important remarks that the features of $PM_{2.5}$ emission during BL and AL are significantly different from each other because it is the CI of the mean difference of the weekly average of $PM_{2.5}$ emission for the pre-and post-lockdown time periods. The results showed that the lockdown had an influential effect on $PM_{2.5}$ emission. Therefore, after lockdown was over, the $PM_{2.5}$ level in the air was less than that for the BL time period.

Relationship between the variables

In this section, we determine the linear relationship between the different types of pollutants so that during the application of RFK, we can skillfully select the important covariates to predict $PM_{2.5}$ emission. In Figure 4, we detect that the

pollutants in the air are highly correlated, and we assume r as the measure of correlation. We observe that the daily $PM_{2.5}$ emission and daily PM_{10} emission during the entire time period are positively correlated, that is, 0.98 which indicates that if $PM_{2.5}$ increases, then PM_{10} will also increase. Similarly NO_2, NO_x are also positively correlated, with a correlation coefficient of 0.91.

<div align="right">Figure 4</div>

Correlation matrix of the variables to detect the degree of association between them
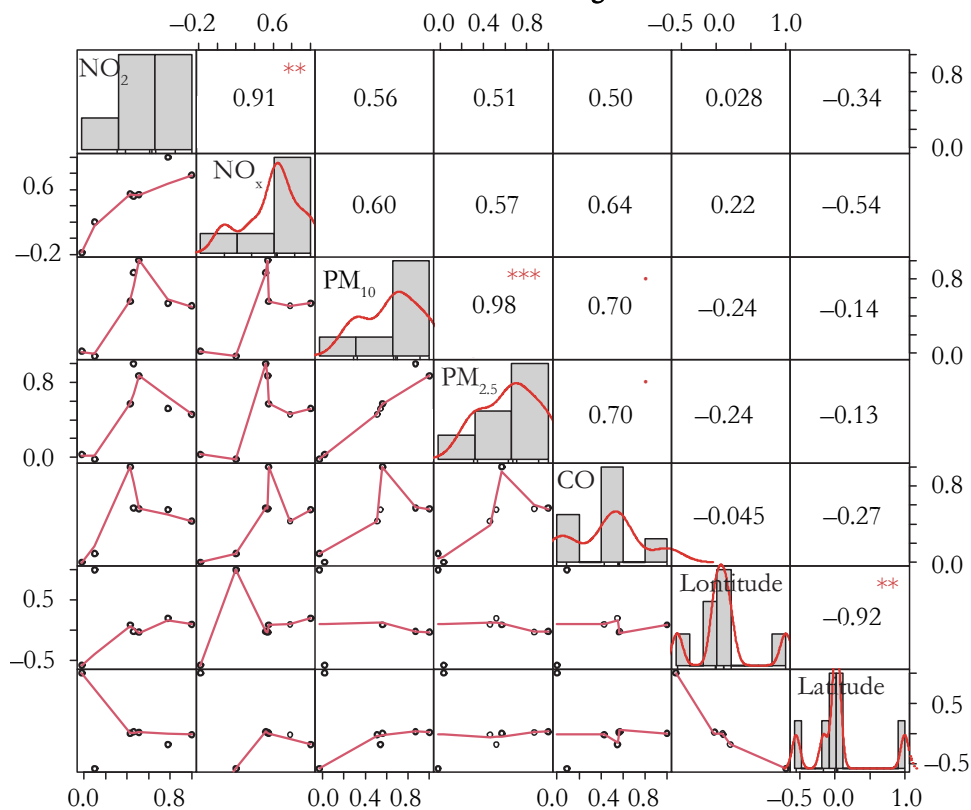
Notes: *** for $p<0.001$, ** for $p<0.01$, * for $p<0.05$, and for $p<0.1$.

Similarly, the daily emissions of PM_{10} and $PM_{2.5}$ are also positively correlated with CO, that is , 0.70. Apart from these, NO_2 is positively correlated with PM_{10} with a correlation coefficient of 0.56. Similarly, NO_2 is positively correlated with $PM_{2.5}$ and CO. The correlation coefficient between NO_2 and $PM_{2.5}$ is 0.51 and that between NO_2 and CO is 0.50. Another important pollutant NO_x is highly correlated with $PM_{2.5}$, with a correlation coefficient of 0.57, and is also positively correlated with PM_{10} with a correlation coefficient of 0.60. The correlation coefficient between NO_x and CO was 0.64. There is no significant correlation between the explanatory variables and the latitude and longitudinal position; however, the missing correlation

Statistical assessment of spatio-temporal impact of Covid-19 lockdown on
air pollution using different modelling approaches in India, 2019–2020

69

between the pollution concentration and the values of the latitudes or longitudes does not guarantee the absence of influence in the case of nearby stations. As a result, any monitoring station can influence the daily pollutant concentrations at another nearby monitoring station. Therefore, we were able to take enough gridded points between two monitoring stations to capture the entire spatial information, which will help interpolate the pollutant concentration on the unobserved locations.

Temporal trend analysis

It is important to analyse whether the data are stationary before opting for a temporal trend analysis. The temporal stationarity of the dataset implies that the temporal association of the variable of a time window is dependent only on the window size. If it is non-stationary, then the association of a time window depends not only on the window size but also on the starting and ending time points. For this reason, the autocorrelation function (ACF) plays a major role if it does not converge toward 0 while the lag or window size is increasing; then, it can be surmised that the time series data is not stationary. Generally, in the stationary dataset, the ACF converges to 0 when the lag is increased. In Figure 5, we study the variation in ACF with respect to the lag starting from 0 to 25.

Figure 5

ACF of the entire data
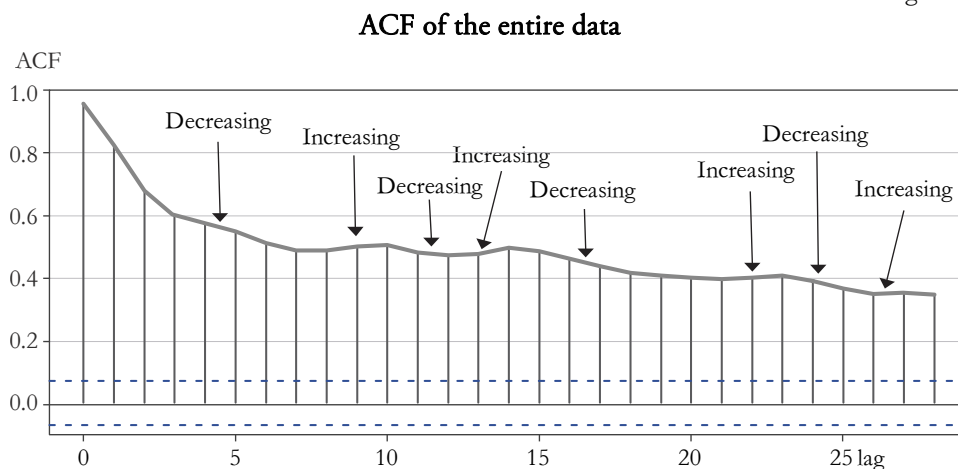
We notice that the ACF decreases and increases alternatively from Figure 5 with respect to lag, and the ACF does not go to 0 while the lag is increasing. Therefore, we can infer that the data are not stationary. It is possible to conclude that the distribution of $PM_{2.5}$ is dependent on the starting and ending time points, and there is a significant correlation of $PM_{2.5}$ values for each day.

As the data are not stationary, seasonality may exist. We now discuss the seasonal influence in each of the major activity zones. For this purpose, we consider February and March as spring; April, May, June, and July as summer; August and

September as monsoon; and October, November, December, and January as winter. In Table 6, we detect that during winter in every zone, the seasonal effect is very high compared to the other seasons. For example, the effects of winter during 2019 on the major activity zones such as transport, residential, commercial, and institutional zones were 60.40, 51.52, 48.07, 56.18 respectively. The values for 2020 are 62.36, 53.78, 50.23, and 58.14, respectively. Likewise, the seasonal influence of monsoon on the transport, residential, commercial, and institutional zones in 2019 were –68.34, –57.44, –55.09, –65.42, and similarly, and those during 2020 were –68.44, –57.27, –55.17, and –65.61, respectively. The positive value of seasonal influence (from Table 6) indicates that there is a positive seasonal trend, and the negative value of seasonal influence indicates that there is a negative seasonal effect on $PM_{2.5}$. For example, in the transport zone during monsoon in the year 2020, the seasonal influence was –68.44, which indicates a decreasing seasonal effect, but during winter, it was 62.36 indicating a positive seasonal impact on daily $PM_{2.5}$ emission. However, owing to the Covid-19 lockdown and restrictions on public transportation, seasonal influence is reduced. Therefore, in the transport zone during spring in the year 2019, the seasonal influence was –2.29, whereas during spring in the year 2020, it was considerably less than the previous one, that is, –3.21. The same feature is also observed in the remaining zones (Table 6). Along with these, we see that every year during winter, average $PM_{2.5}$ value is comparatively higher than that during the monsoon. For example, in the institutional zone, the average $PM_{2.5}$ values reach up to 190.71 μg/m³ during winter, whereas during monsoon, this reaches 41.56 μg/m³.
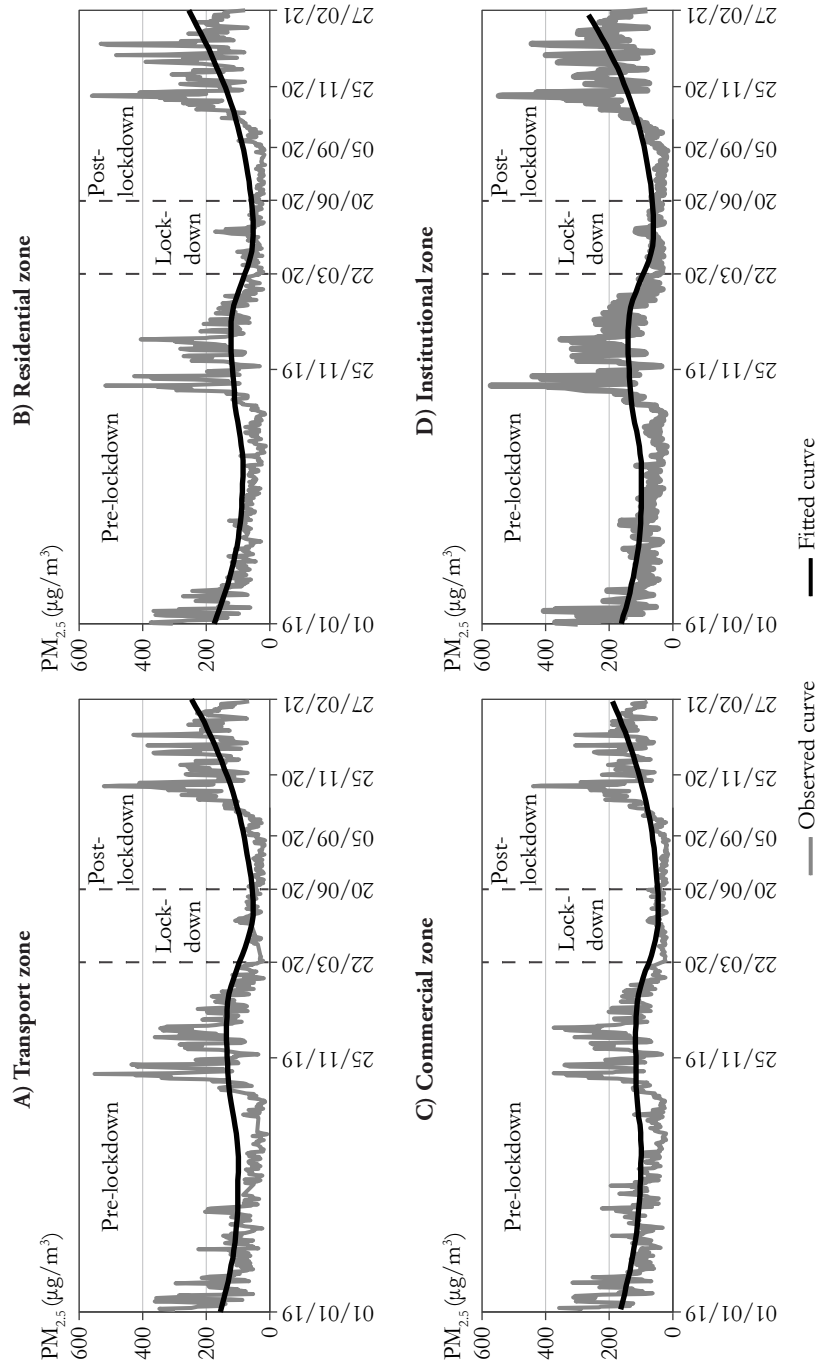
Table 6

Seasonal influence of each season on daily $PM_{2.5}$ emission in four major activity zones

Season	Year	Transport	Residential	Commercial	Institutional
Summer	2019	–54.92	–47.32	–42.70	–52.78
Monsoon	2019	–68.34	–57.44	–55.09	–65.42
Winter	2019	60.40	51.52	48.07	56.18
Spring	2019	–2.29	–2.12	–2.65	2.38
Summer	2020	–54.71	–47.08	–42.48	–52.09
Monsoon	2020	–68.44	–57.27	–55.17	–65.61
Winter	2020	62.36	53.78	50.23	58.14
Spring	2020	–3.21	–2.94	–3.48	0.742

The temporal pattern analysis of the four zones of the daily average of $PM_{2.5}$ values for three described time periods, namely, pre-lockdown, during-lockdown, and post-lockdown, is shown in Figure 6.

Statistical assessment of spatio-temporal impact of Covid-19 lockdown on
air pollution using different modelling approaches in India, 2019–2020

71

Figure 6

Time series trend for four zones during the entire time period

In Figure 6, we can see that in every major activity zone, the trend is decreasing with respect to the time up to the end of monsoon. After the monsoon season, it starts to increase and reaches its maximum, especially at the end of November. However, during the lockdown period, the daily $PM_{2.5}$ value was comparatively lower than that in the summer of the previous year. However, in the post-lockdown time period, the trend started to increase slowly after the monsoon, and it reached the peak in mid-November; however, given the social and transport restrictions, this peak is smaller than the peak point of the year 2019, which is considered pre-lockdown time period, and after winter, it began to decrease. As a result, we can infer (from Figure 6) that, along with the seasonal impact, secular trend, cyclical, and random effects, one more effect is being confounded: the lockdown effect which will be estimated in the later part of this research.

We now compare the average amount of important air quality parameters (such as $PM_{2.5}$, PM_{10}, and AQI) for each of the major activity zones before and during the lockdown period. In this situation, we calculated the average pollutant concentrations and AQI levels for the BL and DL time periods, which are mentioned earlier in Table 5. Then, we subtracted the pre-lockdown average pollutant concentration from the pollutant concentrations during lockdown. We compared this with the average values of the pre-lockdown time and converted it into a percentage. We obtained the average percentage of declination due to lockdown for all major activity zones. This can be formulated as follows.

Average declination

$$= \left(\frac{\text{Mean during lockdown} - \text{Mean of the before lockdown}}{\text{Mean of the before lockdown}} \cdot 100 \right) \%$$

From Table 7, we can see that in every zone, the parameters are reduced to a certain percentage.

Table 7

Percentage of average decrease of $PM_{2.5}$, PM_{10}, and AQI in diferent major-activity zones because of lockdown

(%)

Components	Transport	Residential	Institutional	Commercial
$PM_{2.5}$	–63.79	–61.31	–61.38	–62.13
PM_{10}	–62.19	–54.84	–49.83	–45.73
AQI	–11.11	–29.05	–22.71	–26.76

For example, in the transport zone, the average $PM_{2.5}$ values were reduced by approximately 63.79%, whereas in the transport zone, the average PM_{10} values were reduced by 62.19%, and in the residential zone the average of AQI value declined by almost 29.05% (from Table 7). Due to the lockdown, the weekly average of $PM_{2.5}$ emissions decreased by 62.15%. The weekly average of PM_{10} is reduced by 53.14%, and the weekly average of AQI decreased by 22.40% throughout Delhi.

Statistical assessment of spatio-temporal impact of Covid-19 lockdown on
air pollution using different modelling approaches in India, 2019–2020

73

Spatial trend analysis

Spatial similarity analysis

The prime condition for spatial trend analysis is to crosscheck whether the weekly $PM_{2.5}$ emission changes with the geo-spatial location. In this scenario, spatial auto-correlation plays an important role because if the datasets are spatially auto-correlated, then there exists a similar pattern in $PM_{2.5}$, PM_{10} emission, and other pollutant concentrations in the dataset of nearby locations. If the datasets are not spatially auto-correlated for those cases, the datasets are spatially random, which means that the datasets of two nearby locations are contradictory in pattern to each other. Therefore, when studying the spatial trend, we should consider those datasets which are spatially dependent of each other. If the datasets are spatially random, then we cannot interpolate the $PM_{2.5}$ values for the unobserved locations, using the observed information. Therefore, we must first inspect the spatial autocorrelation. Therefore, the test of spatial autocorrelation is executed at a significance level of 0.05, where Moran's I index (I) is taken as a measure of spatial autocorrelation (Till et al. 2018). Here,

$$H_0: I = 0$$
$$H_1: I \neq 0$$

In particular, during BL, the data for the 12th, 23rd, 25th, and 26th weeks are not spatially auto-correlated, and during DL, the data are not spatially auto-correlated from the 15th week to the 19th week and from the 24th week to the 26th week at 0.05 level of significance as the p-value is less than 0.05. Therefore, we can infer that the datasets for the remaining period are spatially autocorrelated. This is why we observe similar types of characteristics in $PM_{2.5}$ emission in neighbouring locations compared to those locations which are geographically far away. For example, the weekly average data of the important air pollutant concentrations, such as $PM_{2.5}$, PM_{10}, etc. for the 13th week of 2019 are spatially autocorrelated. We studied the patterns of the data and found that Narela is near the monitoring station of Alipur compared to the Karni Singh Shooting Range. As a result, during the 13th week of the year 2019 (considered as BL in Table 5), there was a high correlation between the weekly average of $PM_{2.5}$ in Alipur and Narela (0.98) compared to that of Alipur and Karni Singh Shooting Range (0.93). This test of spatial autocorrelation plays an important role in determining the spatial neighbourhood, which ultimately helps in spatial interpolation in the unobserved location.

Spatial interpolation

Our target was to interpolate the pollutant concentrations at those unobserved locations. In this case, spatial interpolation is a reliable tool. Therefore, for spatial trend analysis resolution, these weekly datasets are taken which are spatially auto-correlated, and the missing data are interpolated using spatial interpolation

techniques. In this study, three types of interpolation techniques, IDW, OK, and RFK, were applied to compare the efficiencies of these interpolation techniques. In IDW, the goodness of interpolation is dependent on the value of p. We inspected the correctness of the IDW interpolation method with respect to two measures, namely the RMSE and R^2 values given in Table 8.

<div align="right">Table 8</div>

RMSE and R^2 changing with the variation of p in IDW

p	RMSE	R^2	p	RMSE	R^2
0.1	21.713862	0.915102	1.1	21.41463	0.917632
0.2	21.5611777	0.916301	1.2	21.585	0.9163575
0.3	21.4079816	0.9175161	1.3	21.76469	0.9149997
0.4	21.2656589	0.9186298	1.4	21.947072	0.9136144
0.5	21.14805	0.9589295	1.5	22.12609	0.9122447
0.6	21.0694	0.959249	1.6	22.29762	0.9109228
0.7	21.0408	0.9593693	1.7	22.4589	0.9096708
0.8	21.06682	0.9202081	1.8	22.608	0.9085022
0.9	21.144	0.9196403	1.9	22.74565	0.9074232
1.0	21.264	0.9187535	2.0	22.8706	0.9064344

From Table 8, it can be concluded that the most favourable value of p in this interpolation procedure is 0.7, because the minimum RMSE is 21.0408. In this scenario, the R^2 value is 0.9593693 (from Table 8) which implies that approximately 96% of the $PM_{2.5}$ data is explained by the IDW method, and it is satisfactory to interpolate the unobserved values. Employing the IDW interpolation approach, the gridded points (0.01^0 by 0.01^0 i.e. 10 km×10 km along longitude and latitude) were interpolated to show the spatial trend for BL and DL. Despite this, the RMSE of IDW for BL is 16.40 whereas that for DL is 12.72 (from Table 9).

<div align="right">Table 9</div>

Comparison between IDW, OK, and RFK corresponding to the spatially autocorrelated weeks in 2019 and 2020 on the basis of RMSE

Sl.No.	Week	Year	IDW	OK	RFK
1	12	2020	15.46	12.53	0.030
2	13	2019	16.73	15.93	0.071
3	13	2020	9.90	9.64	0.011
4	14	2019	18.14	16.32	0.135
5	14	2020	11.91	11.45	0.043
6	15	2019	16.05	14.52	0.069
7	16	2019	9.90	9.53	0.024
8	17	2019	15.87	14.78	0.009
9	18	2019	13.24	14.10	0.069
10	19	2019	28.13	25.38	0.409
11	20	2019	16.40	13.15	0.138
12	20	2020	12.72	11.78	0.442

Statistical assessment of spatio-temporal impact of Covid-19 lockdown on
air pollution using different modelling approaches in India, 2019–2020

75

In OK, the empirical variogram is fitted by several variogram models such as Gaussian, exponential, linear, and spherical, and amidst all of these, the RMSE of the spherical variogram model is minimal, as shown in Table 10 during both periods.

Table 10

Comparison between the performance of different variogram models for 20th week during 2019 and 2020

Sl.No.	Week	Year	Variogram model	RMSE
1	20	2020	Linear	16.50854
2	20	2020	Gaussian	56.982
3	20	2020	Spherical	0.00170
4	20	2020	Exponential	196.3646
5	20	2019	Linear	35.33872
6	20	2019	Gaussian	149.5183
7	20	2019	Spherical	8.940682e-05
8	20	2019	Exponential	494.5034

From Table 10 we find that the RMSE of the spherical variogram model fitting is very low compared to the other variogram models, such as Gaussian, Linear, and Exponential, to capture the variability information due to spatial reasons. During the 20th week of the year 2019, the RMSE was 0.00170 (from Table 10) which indicates that the spherical variogram is capable of detecting the spatial variability compared to the other variogram models. Before fitting the spherical variogram, the important parameters, nugget, sill, and range were estimated, taking into account the minimum RMSE; for example, the RMSE of the spherical variogram fitting on the dataset of 20th week of the year 2019 was 0.0034. Then, using OK, we interpolate the weekly average of $PM_{2.5}$ on the unobserved locations and gridded points. The RMSEs of OK for BL and DL are respectively, 13.15 and 11.78 (from Table 9).

In the RFK model, at the time of performing the RF regression between the variables to predict the $PM_{2.5}$ values, mtry and ntree were taken differently based on Out-Of-Bag (OOB) errors. For example, the mtry of 20th week of 2019 is 4, but for the same week of 2020, the value of mtry is 3, but the ntree is the same, that is, 1,000 for both periods. In addition, the value of G (Han et al. 2016) is plotted along the x-axis in Figure 7, and along the y-axis, the names of the variables are plotted. We distinguished that the first three important variables for this RFK model for 20th week 2019 were latitude, PM_{10}, and longitude, whereas those of the 20th week 2020 were PM_{10}, CO, and longitude. Therefore, during the 20th week of 2020, the variation in $PM_{2.5}$ emission with respect to the variation in latitude, is not very effective.

Figure 7

Plotting of Variable importance, that is, Gini-Mean decrease of explanatory variables (used in RFK) in descending order

A) Before lockdown   B) During lockdown
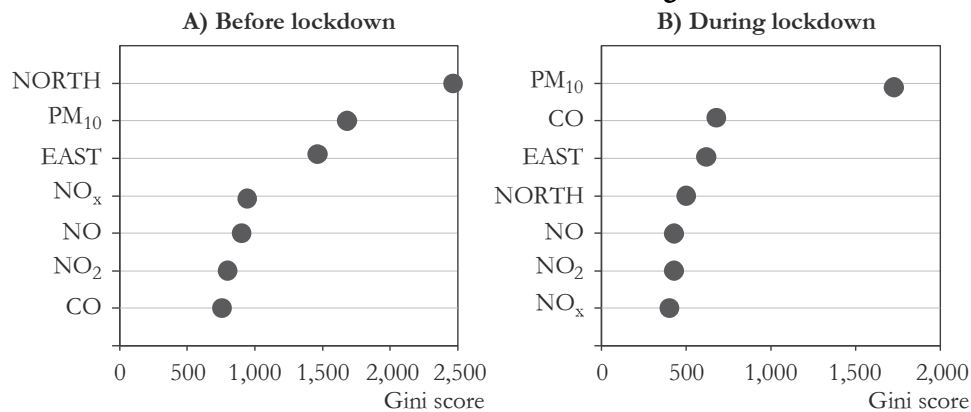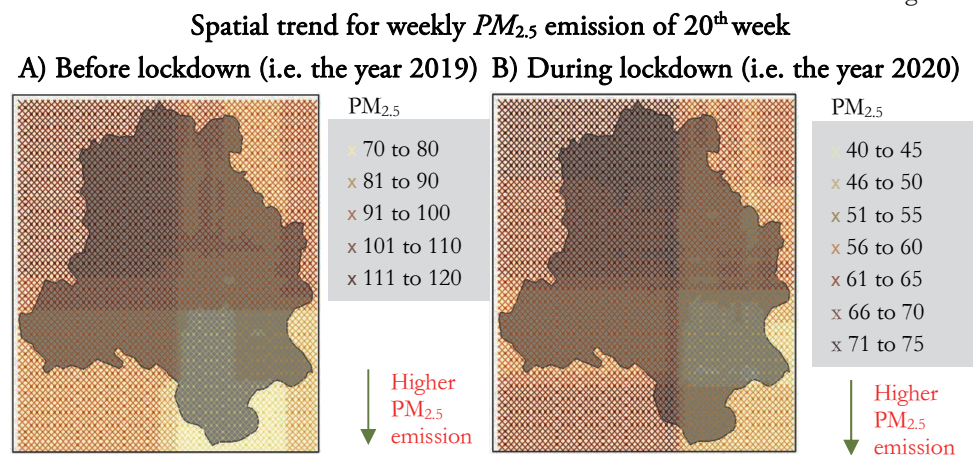
From Figure 7 A) we can say that latitude is the most important variable in RFK, and in Figure 7 B) PM_{10} is the most important variable in the RF regression. Moreover, during the 20th week of 2019 and 2020, latitude was positively correlated (0.223), whereas longitude was negatively correlated (–0.33) with $PM_{2.5}$. It implies that if we move along the eastern direction, then pollution decreases with increasing longitude, whereas if we move along the northern direction, the density of $PM_{2.5}$ increases. Therefore, we can infer that the risk of air pollution in northern Delhi is more sensitive than that in the eastern part of Delhi. Thereafter, in RFK, after employing ion, the empirical variogram of OOB errors is fitted with a spherical variogram model. The important parameters of the variogram: nugget, sill, range, and the corresponding RMSE are respectively 22.1, 47, 0.28, and 0.013 for the 20th week of 2019, whereas for the 20th week of 2020, the estimates of those parameters are 3, 24.45, 0.28, respectively and RMSE is 0.0057. In Figure 8 A) and 8 B), the spatial trend of BL and DL of 20th week is shown as the data for this week is spatially auto-correlated (validated by I). In this contour plot, we plotted longitude, latitude, and interpolated $PM_{2.5}$ values along the x-axis, y-axis, and z-axes, respectively.

The interpolated value was calculated for both periods after fitting the spherical variogram of OOB errors. The contour plot in Figure 8 shows the spatial variation in the effect of lockdown across the whole of Delhi. From Figure 8 A), it is observed that the highest contour line crosses 120 µg/m³ which means that the maximum weekly $PM_{2.5}$ concentration during the 20th week of the year 2019 reaches 120 µg/m³. Similarly, the maximum $PM_{2.5}$ density is in 80–95 µg/m³ [from Figure 8 A)], but from Figure 8 B), it has been confirmed that the maximum contour line is 65 µg/m³ and the maximum density is in 50–60 µg/m³ during the 20th week of the

Statistical assessment of spatio-temporal impact of Covid-19 lockdown on
air pollution using different modelling approaches in India, 2019–2020

77

year 2020. During the pre-lockdown period, in the northwestern part of Delhi, the $PM_{2.5}$ level was higher compared to the other parts of Delhi. In particular, $PM_{2.5}$ emission is the highest in the locations near Bawana, Delhi, whereas in this region during the lockdown period, the $PM_{2.5}$ emission level is much lower than before the lockdown [from Figure 8 A)]. Moreover, Narela, Bawana, Sector 5, Bakoli, Bhaktwarpur, etc. in North Delhi are the main hot spot areas of $PM_{2.5}$ emission. Therefore, the AQI level in the northern part of Delhi was very high at 185. This indicates that people in these regions are at a high risk of acute respiratory problems. The RMSE of the RFK model for the 20th week of 2019 was 0.138, whereas that for the same week in 2020 was 0.442. In Table 9, the entire comparison between the three well-known spatial interpolation models and RFK interpolates admirably because of its minimum RMSE. After using RFK interpolation, we estimated the $PM_{2.5}$ values at the unobserved location for both periods.

Figure 8

Spatial trend for weekly $PM_{2.5}$ emission of 20th week

A) Before lockdown (i.e. the year 2019) B) During lockdown (i.e. the year 2020)

Note: The green line indicates the weekly higher $PM_{2.5}$ emissions from weekly lower $PM_{2.5}$ emissions.

Spatio-temporal behaviour analysis

Spatio-temporal impact of lockdown

In this section, we describe the spatio-temporal intervention of the lockdown and the spatio-temporal characteristics of each monitoring station. Using the DID estimator (β_3) from equation (5) we estimated the measure of intervention of lockdown in $PM_{2.5}$ emission in every major activity zone. In Table 11, we studied the regression coefficient of the DID regression, and in the bracket, the standard error of this estimation is discussed.

Measurement of the intervention of lockdown using DID estimator

Zone	DID estimator (β_3)	p-value (H_0: β_3=0)
Transport	−8.13	0.00876**
Residential	−0.46	0.23854
Commercial	−2.78	0.039**
Institutional	−1.40	0.0079*

Notes: *** for p<0.001, ** for p<0.01, * for p<0.05, and for p<0.1.

From Table 11, we observe that in the transport zone, the lockdown has a negative impact (−8.13), meaning that because of the lockdown in this zone, there is a huge restriction regarding transportation, which helps to mitigate the $PM_{2.5}$ emission. This intervention is significant at 0.1 level, which means that almost 90% of areas under transport zones have a strict declination in $PM_{2.5}$ emission due to lockdown. Likewise, the lockdown also had a significant negative effect on commercial (−2.78) and institutional zones (−1.40), which was significant at 0.1 level, respectively. However, in the residential zone, the lockdown had minimum negative intervention (−0.46), and it was significant at 0.1 level. In the transport zone, this negative influence is the maximum compared with the other zones. Therefore, lockdown in the transport zone is an effective measure for controlling AQI levels.

Spatio-temporal behaviour of monitoring stations

In this section, we discuss the spatio-temporal behaviour of each monitoring station to study the trend of $PM_{2.5}$ emissions during the four seasons. As a result, we are able to understand the spatio-temporal features of AQI levels in the neighbourhood of each monitoring station. From Table 12, we detect that in every monitoring station during winter, the MK τ is positive, which indicates that we should be careful about the air pollution during the winter season except in IHBAS, Dilshad Garden, where the MK τ is −0.018, which is satisfactory because it means that in this region and its neighbourhood the $PM_{2.5}$ emission is low. This helps to maintain healthy AQI. Among all of the monitoring stations and their neighbourhoods, the trend of $PM_{2.5}$ is highly positive; for example, in DTU, the MK τ is 0.1 and in Dwarka, it is 0.156. Similar statistics are seen in Mundka (0.123), Karni Singh Shooting Range (0.123), and Ayanagar (0.138) which are risky in terms of $PM_{2.5}$ emission (from Table 12). Similarly, in summer and spring, the MK τ for almost all monitoring stations were negative. Therefore, the AQI values during the summer and spring were satisfactory and healthy. However, during the monsoon in some monitoring stations and their neighbourhoods, the trend of $PM_{2.5}$ emission is decreasing, and in other monitoring stations, the trend is the opposite. For example, during the monsoon in Burari Crossing (MK τ =0.33), the air quality is poorer than

Statistical assessment of spatio-temporal impact of Covid-19 lockdown on
air pollution using different modelling approaches in India, 2019–2020

79

that of Dwarka (MK τ =–0.046) (from Table 12). Thus, we analysed the spatio-
temporal features of each monitoring station and its neighbourhood.

Table 12

Value of MK τ for monitoring stations of BL and DL

Monitoring stations	Winter	Spring	Summer	Monsoon
Alipur	0.046	–0.28	–0.408	0.0312
AnandVihar	0.069	–0.28	–0.39	–0.035
AshokVihar	0.068	–0.35	–0.49	0.068
Ayanagar	0.138	–0.30	–0.17	0.114
Bawana	0.088	–0.27	–0.46	0.12
Burari Crossing	0.0018	–0.26	–0.43	0.33
CRRI mathura road	0.028	–0.19	–0.32	–0.067
DTU	0.1	–0.25	–0.34	0.033
Dwarka	0.156	–0.066	–0.374	–0.046
IGI Airport	0.082	–0.28	–0.41	–0.10
IHBAS, Dilshad Garden	–0.018	–0.27	–0.301	–0.29
ITO, Delhi	0.078	–0.33	–0.43	–0.037
Jahangirpuri, Delhi	0.09	–0.28	–0.44	–0.00437
Jawaharlal Nehru stadium, Delhi	0.095	–0.458	–0.408	0.072
Karni Singh Shooting range	0.141	–0.372	–0.417	0.094
Lodhi Road, Delhi	0.0614	–0.324	–0.195	0.102
Major Dhyan Chand National Stadium, Delhi	0.058	–0.363	–0.376	0.021
Mandir Marg, Delhi	0.086	–0.416	–0.322	0.0579
Mundka, Delhi	0.123	–0.168	–0.452	0.0465
Najafgarh, Delhi	0.0584	–0.247	–0.469	0.0842
Narela, Delhi	0.0451	–0.288	–0.361	0.082
Nehru Nagar, Delhi	0.094	–0.483	–0.393	–0.000547
North Campus, DU, Delhi	0.053	–0.347	–0.463	–0.0514
NSIT Dwarka, Delhi	0.11	–0.121	–0.371	–0.054
Okhla Phase	0.094	–0.324	–0.40	0.0164
Patparganj, Delhi	0.0894	–0.378	–0.247	–0.011
Punjabi Bagh, Delhi	0.043	–0.395	–0.417	–0.0142
Pusa, Delhi	0.111	–0.472	–0.38	0.0536
R K Puram, Delhi	0.0063	–0.38	–0.174	–0.00984
Rohini, Delhi	0.0753	–0.301	–0.407	0.094
Shadipur, Delhi	0.0504	–0.348	–0.371	–0.0719
Sirifort, Delhi	0.0889	–0.299	–0.42	0.169
Sonia Vihar, Delhi	0.0188	–0.371	–0.333	–0.0437
Sri Aurobindo Marg, Delhi	0.0897	–0.397	–0.36	0.0771
Vivek Vihar, Delhi	0.091	–0.35	–0.393	0.0361
Wazirpur, Delhi	0.0648	–0.445	–0.424	0.161

In Table 12, the value of Mann–Kendall's τ over two time periods for monitoring stations is discussed at a 0.95 level of confidence. We can discern that the temporal trend diminishes almost every time, except for a few monitoring stations, such as in Lodhi road, where the trend is increasing for two time periods, and in Karni Singh, where the trend is increasing in DL.

As a result, the pollution of the entire Delhi region was diluted compared to the previous years. However, RFK performs better than other interpolation models, but some inescapable flaws stipulate further exploration of previous research methodologies, and we admit the restrictions of our research; for example, we have ignored the impact of serious meteorological factors such as wind speed and wind direction on $PM_{2.5}$ emission. However, this type of statistical approach has a significant disadvantage; it does not involve the impact of the changing characteristics of the atmosphere, such as wind speed and direction and depth of the inversion layer.

Conclusions

This study examined the temporal and spatial patterns of pollutant concentrations throughout the year. We are not only restricted to the important features of pollutant concentration, but we also focus on the spatio-temporal impact of lockdown on air pollution. From the above discussion, we can see that the pollution level of the BL period strongly differs from that of the AL period. There is a huge variation in $PM_{2.5}$ emission in Delhi. During the monsoon season in Delhi, pollution was minimal in the transport zone. In winter, pollution is at its maximum in the transport zone. In addition to seasonal influence, there is a significant secular trend, and cyclic behaviour is observed in 24 hour $PM_{2.5}$ emissions in Delhi. The average pollutant emission in Delhi decreased by approximately 60% because of lockdown, but the lockdown is not the sole factor responsible for this decline. The season also helps decrease the pollutant concentrations in the air. As the daily $PM_{2.5}$ emissions are not completely spatially dependent, there is a serious limitation of the spatio-temporal interpolation techniques for predicting the same. Among the three previously mentioned spatial interpolation techniques, RFK performed better than the other models. Moreover, in the northwestern part of Delhi, the pollution level is serious, and the AQI is very unhealthy, especially in Ayanagar, Dwaraka, Narela, and Bawana Sector 5. In addition to the spatial and temporal cross-sectional discussion about the influence of lockdown, we measured the spatio-temporal intervention of lockdown on pollutant concentration simultaneously, and it indicated that the transport zone was the most affected zone. One of the future directions of this research is to use copulas to find the joint probability distribution function of the covariates, helping us compute the Bayesian risk of wind speed and wind direction of $PM_{2.5}$ concentration. We could not establish a testing procedure for spatial

Statistical assessment of spatio-temporal impact of Covid-19 lockdown on
air pollution using different modelling approaches in India, 2019–2020

81

stationarity. Consequently, some portions of the data have an ill-conditioned covariance matrix. Therefore, we can model the data spatially and temporally simultaneously using ML techniques to construct a spatial-temporal model.

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air pollution using different modelling approaches in India, 2019–2020

83

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