

## Modeling Temporal Variation of Particulate Matter Concentration at Three Different Locations of Delhi

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### Authors' contributions

This work was carried out in collaboration among all authors. Authors DR and AR planned the experiment. Author DR performed the analysis and wrote the paper. Author AR interpreted the outcome and wrote the paper. Authors KA, SA and Vishwanath helped in data collection and paper writing. All authors read and approved the final manuscript.

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### ABSTRACT

**Aims:** To model the concentration variation of PM<sub>2.5</sub> and PM<sub>10</sub> in selected locations of Delhi.

**Study Design:** ARFIMA-GARCH model.

**Place and Duration of Study:** The study was conducted by using daily (24 hour interval) data of PM<sub>2.5</sub> and PM<sub>10</sub> concentration from three air quality monitoring stations of Delhi namely, Narela, Okhla Phase II and Pusa.

**Methodology:** The ARFIMA model is applied as the mean model and the GARCH model as the variance model.

**Results:** The selected series are stationary and exhibit the presence of long memory in the mean structure. Due to the presence of long memory in mean, the ARFIMA model is applied. The residual

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series have conditional heteroscedasticity. Hence, the GARCH model is applied as a variance model. The fitted models are validated using RMSE, MAE and MAPE.

**Conclusion:** The concentration variation of PM<sub>2.5</sub> and PM<sub>10</sub> followed long memory process in mean structure. ARFIMA-GARCH model satisfactorily explained the variation of concentration.

*Keywords:* ARIMA; GARCH; particulate matter; pollution; time series; volatility.

## 1. INTRODUCTION

The greatest environmental health concern in the modern world is exposure to polluted air [1]. Particulate matters, or PMs for short, are the air pollutants that have the worst effects on human health. Particulate matter is a term used to describe small solids or liquid droplets that enter the human body through the air we breathe and may have either anthropogenic or natural origins. Particles with a diameter of 2.5 to 10 µm (PM<sub>10</sub>) can penetrate deep inside the lung, whereas PM<sub>2.5</sub> particles can enter the circulatory system after breaching the lung barrier. One of the most current estimates on mortality brought on by PMs suggests that, globally, fossil fuel-generated PM<sub>2.5</sub> is responsible for about 8.7 million premature deaths [2]. India is a major contributor as well as victim of air pollution as it is the third largest emitter of greenhouse gases [3] and the fifth largest emitter of PM<sub>2.5</sub> [4]. In reality, according to the World Health Organization's Air Quality Guidelines, none of the Indian cities have achieved the standard for annual PM<sub>2.5</sub> concentration of 5 µgm<sup>-3</sup> [5]. Air pollution is India's second-leading cause of mortality and morbidity, after malnutrition [6]. In India, 17.8% of deaths in 2019 were attributed to air pollution, with outdoor particulate matters responsible for 58.7% of those deaths [7].

Out of the fifteen most polluted cities in the world with respect to annual average PM<sub>2.5</sub> level, ten are situated in India and eight of them are located in the Delhi-National Capital Region (NCR) [8]. According to the 2021 World Air Quality Report, New Delhi is the fourth most polluted city in the world and the most polluted capital city. It has been well documented that every year since last few decades the average annual PM<sub>2.5</sub> concentration in Delhi crosses the annual National Ambient Air Quality Standard of 40 µgm<sup>-3</sup> (which is eight times higher than the WHO's standard limit) [1]. However, despite the adoption of a number of interventions by the government agencies, none of the actions proved to be effective for Delhi-NCR.

Prediction of future particulate matter levels play a crucial role in policy formulation of any country, especially those falling under low- and medium-income group. The present work explores the variation in the concentration of PM<sub>10</sub> and PM<sub>2.5</sub> at different sites of Delhi having different pollution signatures. A proper understanding about the concentration of PM<sub>10</sub> and PM<sub>2.5</sub> and their variation over different times of a year can be helpful for the policymakers to take proactive actions to minimize the hazard. Time series modeling approaches are used for the concentration variation study. A time series is the collection of realizations of any variable over a period of time. The most important characteristic of a time series is that the successive realizations are dependent. The time series analysis is pioneered by Box and Jenkins' [9] Autoregressive Integrated Moving Average (ARIMA) methodology. In several instances it is seen that the realizations of a time series exhibit long term dependencies. This phenomenon is known as the long memory property. If any time series exhibits the long memory property in its mean structure, then instead of ARIMA model, Autoregressive Fractionally Integrated Moving Average (ARFIMA) model [10] is used. The potential presence of long memory in a time series can be tested using [11] GPH statistic. The ARIMA/ARFIMA is a linear model. To address the non-linearity of a time series the Autoregressive Conditional Heteroscedastic (ARCH) [12] and Generalized ARCH (GARCH) [13] models can be used as variance model along with the ARIMA/ARFIMA model as mean model.

## 2. MATERIALS AND METHODS

### 2.1 ARFIMA Model

An ARIMA model is represented as ARIMA ( $p, d, q$ ) where  $p$ ,  $d$  and  $q$  represents the order of autoregression, integration (differencing), and moving average respectively. For a linear univariate time series process  $\{y_t\}$ , the ARIMA process is represented as

$$\varphi(L)(1-L)^d y_t = \theta(L)\varepsilon_t \quad (1)$$

where,  $y_t$  is the actual observation and  $\varepsilon_t$  is the error term observed at time  $t$  such that  $\varepsilon_t \sim IID(0, \sigma^2)$ .  $\varphi(L)$  and  $\theta(L)$  are the polynomial of lag operator  $L$  of order  $p$  and  $q$  respectively. In ARIMA methodology, the order of differencing  $d$  is considered as an integer. The only difference of the ARFIMA model is that here  $d$  has a fractional value. For the ARFIMA models, the fractional parameter  $d$  lies between -0.5 and 0.5 [14].

### 2.2 The ARCH and GARCH Model

A process  $\{\varepsilon_t\}$  is said to have an ARCH ( $q$ ) model if the conditional distribution of  $\{\varepsilon_t\}$  given the available information  $(\psi_{t-1})$  up to  $t - 1$  time epoch can be represented as:

$$\varepsilon_t | \psi_{t-1} \sim N(0, h_t) \text{ and } \varepsilon_t = \sqrt{h_t} v_t \quad (2)$$

where,  $v_t$  is known as innovation and it is independently and identically distributed (IID) with zero mean and unit variance. The distribution of innovation is data specific.

The conditional variance  $h_t$  for an ARCH ( $q$ ) is represented as

$$h_t = \alpha_0 + \sum_{i=1}^q \alpha_i \varepsilon_{t-i}^2, \alpha_0 > 0, \alpha_i \geq 0 \forall i \text{ and } \sum_{i=1}^q \alpha_i < 1 \quad (3)$$

For satisfactory model precision, a large number of parameters are needed for an ARCH model. The GARCH model overcome this problem.

The conditional variance of a GARCH ( $p, q$ ) model is defined as

$$h_t = \alpha_0 + \sum_{i=1}^q \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^p \beta_j h_{t-j}$$

provided  $\alpha_0 > 0, \alpha_i \geq 0 \forall i, \beta_j \geq 0 \forall j \quad (4)$

The GARCH ( $p, q$ ) process is said to be weakly stationary if and only if

$$\sum_{i=1}^q \alpha_i + \sum_{j=1}^p \beta_j < 1 \quad (5)$$

### 2.3 Data Description

Data for  $PM_{2.5}$  and  $PM_{10}$  concentration ( $\mu g m^{-3}$ ) was collected at 24 hours interval from Central Pollution Control Board (CPCB) website (<https://app.cpcbcr.com/ccr/#/caaqm-dashboard-all/caaqm-landing/caaqm-comparison-data>) for three Delhi Pollution Control Committee (DPCC)-regulated air quality monitoring stations situated at Narela, Okhla Phase-II and Pusa Road. These three sampling locations represent the northern (Narela), central (Pusa) and southern (Okhla Phase-II) Delhi. The major source of pollution in Narela and Okhla Phase-II are industrial emission and that in Pusa is vehicular emission. Locations of these three weather monitoring stations have been shown in Fig. 1. The collected data spanned over the period of 01 July 2018 to 31 July 2022 (1492 datapoints). The whole data set is divided into two sets namely model building set and model validation set. The last ten observations are used for the validation set and the remaining portion as the model building set.

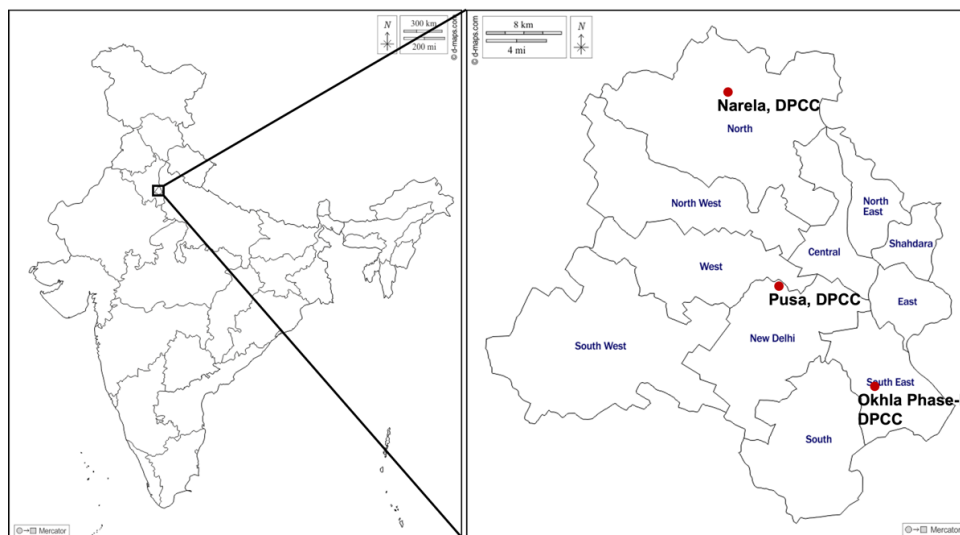


Fig. 1. Map showing the locations of the sampling stations (Narela, Pusa and Okhla Phase-II) in Delhi

### 2.4 Validation

The efficacy of model is tested using three error functions namely, Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE). These error functions are calculated as

$$RMSE = \left[ \frac{1}{T} \sum_{t=1}^T (y_t - \hat{y}_t)^2 \right]^{1/2} \tag{6}$$

$$MAE = \frac{1}{T} \sum_{t=1}^T |y_t - \hat{y}_t| \tag{7}$$

$$MAPE = \frac{1}{T} \sum_{t=1}^T \frac{|y_t - \hat{y}_t|}{y_t} \times 100 \tag{8}$$

where,  $y_t$  is the actual value,  $\hat{y}_t$  is the predicted value and  $T$  is the horizon of forecast.

### 3. RESULTS AND DISCUSSION

The descriptive statistics of  $PM_{2.5}$  and  $PM_{10}$  concentration for the selected location is given in Table 1. It is seen that the mean, median and minimum concentration for both the pollutants follow Narela > Okhla > Pusa. The maximum concentration of  $PM_{2.5}$  follows the same order. But the maximum concentration of  $PM_{10}$  follows a different order. The  $PM_{10}$  concentration has relatively higher S.D. and lower C.V., skewness and kurtosis than the concentration of  $PM_{2.5}$  for all three locations. Even kurtosis of  $PM_{10}$  at Narela is slightly negative. The time plot of  $PM_{2.5}$  and  $PM_{10}$  concentration is given in Fig. 2. For all the three locations, the PM concentration remained comparatively high between late-October to early-January and November was the month with highest average PM concentration which coincides with the period of densest air, least precipitation and, more importantly, this is the peak period of crop residue burning in Delhi and nearby states such as Haryana, Uttar

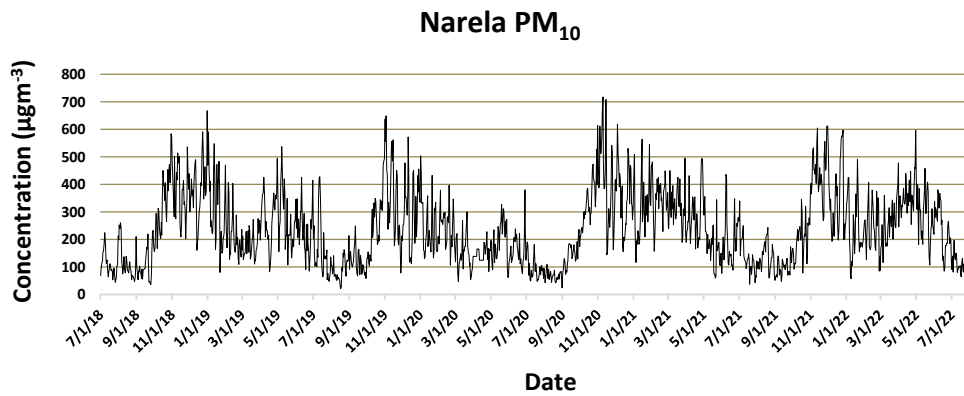
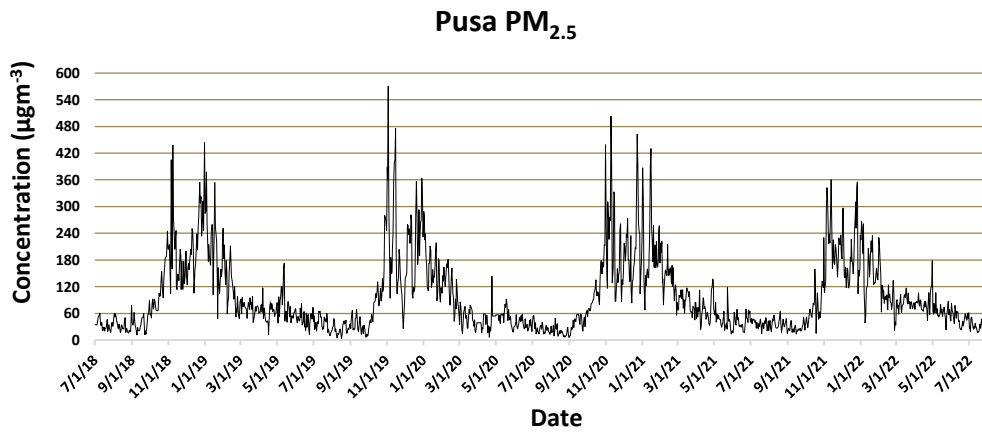
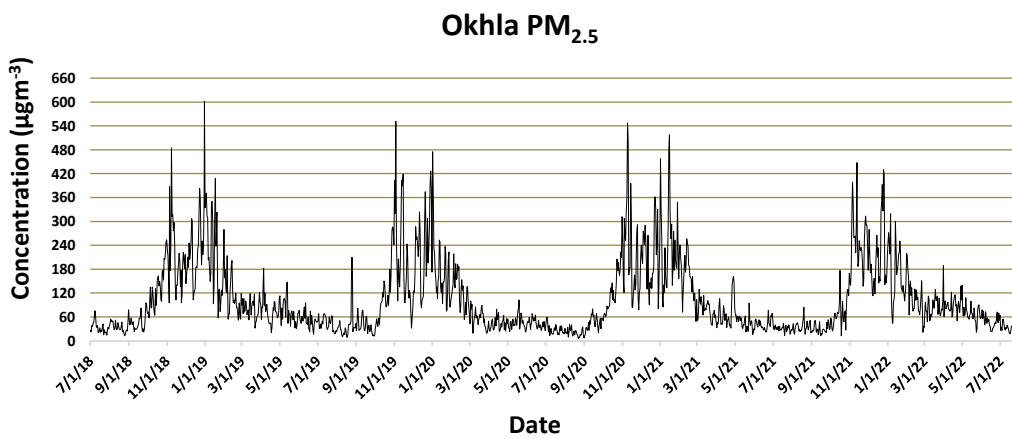
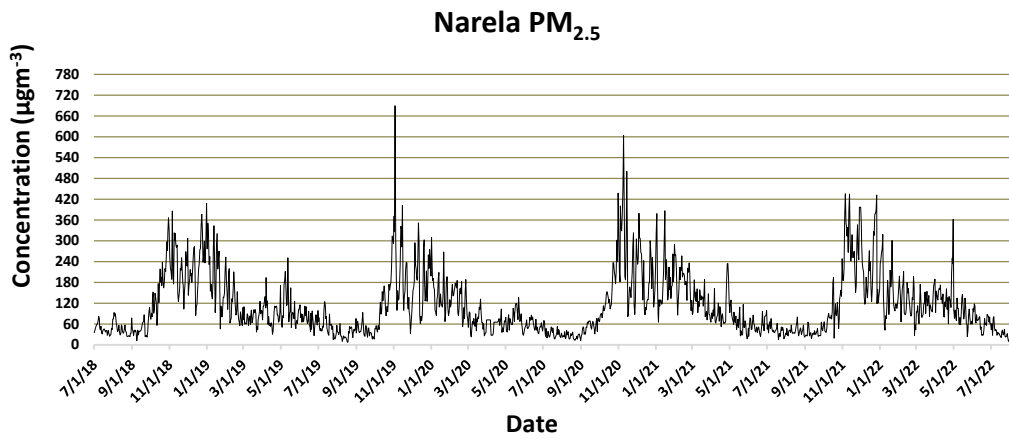
Pradesh and Punjab. Both  $PM_{2.5}$  and  $PM_{10}$  showed comparatively low concentration between early-July to Mid-September. It is during this time in a year when the daily  $PM_{2.5}$  and  $PM_{10}$  concentrations were kept (almost) consistently below the safe limits, 60 and 100  $\mu g m^{-3}$ , respectively, as prescribed in Indian National Ambient Air Quality Standards. August was the safest month with respect to PM pollution as in this month Delhi receives maximum precipitation, which, firstly, makes the air cleaner by bringing down the particulate matters with itself and, secondly, the moisture reduces the density of air thus, making its circulation faster.

The Shapiro-Wilk test [15] is used to determine if the selected series are normally distributed. For the Shapiro-Wilk test, the null hypothesis is  $H_0$ : The series follows normal distribution; against the alternative hypothesis  $H_1$ : The series does not follow normal distribution. It is seen that (Table 2) none of the selected series follow normal distribution at 1% level of significance. Hence, we reject the null hypothesis. The generalized error distribution (GED) is a robust class of distribution. It is considered that all the series follow GED and also the innovations.

The stationarity of the time-series data is tested using Augmented Dickey-Fuller (ADF) test [16] and Phillips-Perron (PP) test [17]. For ADF and PP tests, the null hypothesis is  $H_0$ : Unit root is present in the time series; against the alternative hypothesis  $H_1$ : Unit root is not present in the time series. From the Table 3, it can be seen that for all the selected series both the tests are significant. Hence, we reject the null hypothesis. Both the tests confirm (Table 3) that all the selected series are stationary.

**Table 1. Descriptive statistics of  $PM_{2.5}$  and  $PM_{10}$  concentration for the selected locations**

| Statistics   | Narela     |           | Okhla      |           | Pusa       |           |
|--------------|------------|-----------|------------|-----------|------------|-----------|
|              | $PM_{2.5}$ | $PM_{10}$ | $PM_{2.5}$ | $PM_{10}$ | $PM_{2.5}$ | $PM_{10}$ |
| Observations | 1492       | 1492      | 1492       | 1492      | 1492       | 1492      |
| Mean         | 112.56     | 234.64    | 101.55     | 214.95    | 95.07      | 203.05    |
| Median       | 85.35      | 209.33    | 68.06      | 191.86    | 66.20      | 188.77    |
| Minimum      | 6.62       | 20.48     | 6.29       | 15.52     | 3.44       | 9.97      |
| Maximum      | 689.1      | 717.35    | 601.80     | 884.8     | 570.61     | 726.86    |
| S.D.         | 87.63      | 131.40    | 90.00      | 128.90    | 81.33      | 120.55    |
| C.V. (%)     | 77.85      | 56.00     | 88.62      | 59.97     | 85.54      | 59.37     |
| Skewness     | 1.55       | 0.72      | 1.75       | 0.93      | 1.68       | 0.73      |
| Kurtosis     | 3.02       | -0.04     | 3.41       | 0.8       | 3.29       | 0.34      |



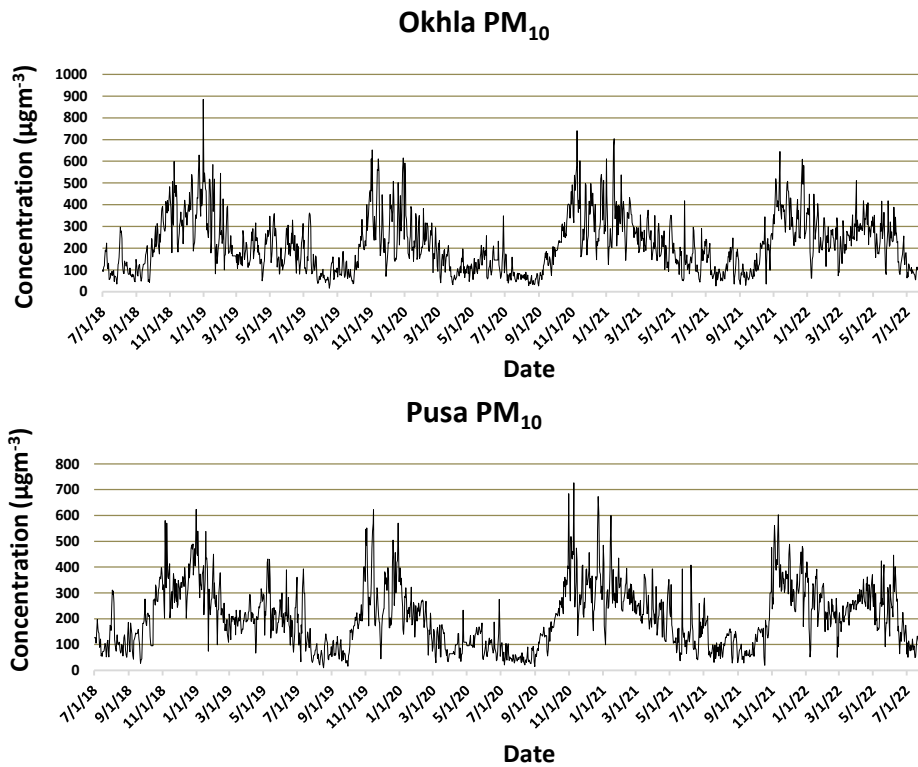


Fig. 2. Time plot of PM<sub>2.5</sub> and PM<sub>10</sub> concentration for the selected locations

Table 2. Test for normality (Shapiro-Wilk test)

| Site Series    | Narela            |                  | Okhla             |                  | Pusa              |                  |
|----------------|-------------------|------------------|-------------------|------------------|-------------------|------------------|
|                | PM <sub>2.5</sub> | PM <sub>10</sub> | PM <sub>2.5</sub> | PM <sub>10</sub> | PM <sub>2.5</sub> | PM <sub>10</sub> |
| Test statistic | 0.857             | 0.950            | 0.813             | 0.937            | 0.832             | 0.955            |
| p-value        | <0.001            | <0.001           | <0.001            | <0.001           | <0.001            | <0.001           |

Table 3. Test for stationarity of the selected series

| Site Test | Narela            |                   | Okhla             |                   | Pusa              |                  |
|-----------|-------------------|-------------------|-------------------|-------------------|-------------------|------------------|
|           | PM <sub>2.5</sub> | PM <sub>10</sub>  | PM <sub>2.5</sub> | PM <sub>10</sub>  | PM <sub>2.5</sub> | PM <sub>10</sub> |
| ADF       | -3.922<br>(0.01)  | -4.429<br>(0.01)  | -3.654<br>(0.03)  | -3.944<br>(0.01)  | -3.587<br>(0.03)  | -3.829<br>(0.02) |
| PP        | -9.686<br>(0.01)  | -10.890<br>(0.01) | -9.468<br>(0.01)  | -10.307<br>(0.01) | -8.811<br>(0.01)  | -9.449<br>(0.01) |

p-value is in parenthesis

The statistical dependencies among the realizations of a time series can be inspected by using the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) plots. The ACF plots (up to 100 lags) of the selected series are given in Fig. 3. From this figure, it can be seen that the ACFs are significant for a large lags. This is known as the hyperbolic decay of ACF. This clearly indicates the presence of long memory in the mean structure. Hence, the ARFIMA model is applied to the data set, instead of the ARIMA model.

Various orders of autoregression and moving average of the ARFIMA ( $p, d, q$ ) model are applied to each series. The residuals are obtained and are tested using the ARCH-LM test for the potential presence of conditional heteroscedasticity. For the ARCH-LM test, the null hypothesis is  $H_0$ : The ARCH effect is not present in the residual series; against the alternative hypothesis  $H_1$ : The ARCH effect is present in the residual series. For each instances, the ARCH-LM test is significant. Hence, we reject the null hypothesis. After that

the GARCH(1,1) model is fitted to the residual series and the best performed order of autoregression and moving average is chosen based on minimum values of Akaike Information Criterion (AIC) and Bayesian information Criterion (BIC). The estimated parameters of the selected ARFIMA ( $p, d, q$ )- GARCH(1,1) models are given in Table 4. It can be seen that almost all the estimated parameters are significant at 1% level of significance. The visualization of observed vs. fitted values is given in Fig. 4. The residual

series are tested for the presence variability that can be explained further. It is seen that all the residual series are white noise (WN). This proved that the selected ARFIMA ( $p, d, q$ )- GARCH(1,1) models are appropriate for forecasting the data under study. The forecast efficiency of the selected models is validated (Table 5) in the model validation set using three error functions namely RMSE, MAE and MAPE. It is seen that the values of these error functions are within permissible limit. Hence, the performances of the selected models are satisfactory.

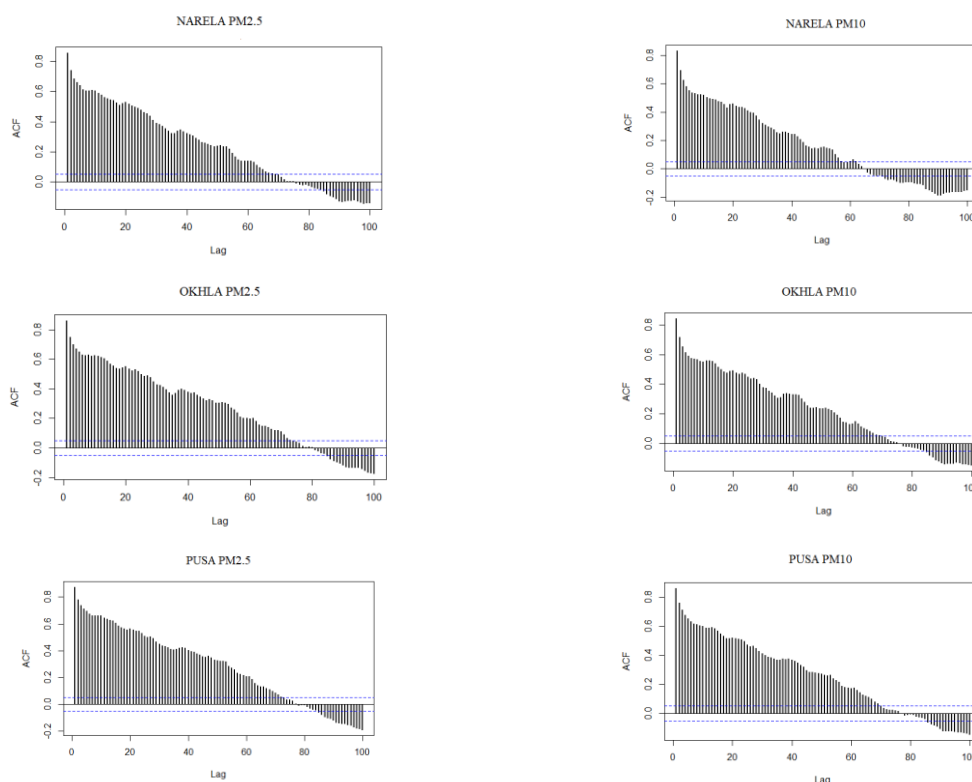


Fig. 3. The ACF plots of the selected series

Table 4. Estimate of parameters of the selected models

|                   | Narela                 |                        | Okhla                  |                        | Pusa                   |                        |
|-------------------|------------------------|------------------------|------------------------|------------------------|------------------------|------------------------|
|                   | PM <sub>2.5</sub>      | PM <sub>10</sub>       | PM <sub>2.5</sub>      | PM <sub>10</sub>       | PM <sub>2.5</sub>      | PM <sub>10</sub>       |
| Model             | ARFIMA<br>(1, $d$ , 2) | ARFIMA<br>(2, $d$ , 2) | ARFIMA<br>(1, $d$ , 2) | ARFIMA<br>(1, $d$ , 2) | ARFIMA<br>(1, $d$ , 2) | ARFIMA<br>(2, $d$ , 1) |
| Variable          | GARCH<br>(1,1)         | GARCH<br>(1,1)         | GARCH<br>(1,1)         | GARCH<br>(1,1)         | GARCH<br>(1,1)         | GARCH (1,1)            |
| <b>Mean Model</b> |                        |                        |                        |                        |                        |                        |
| Constant          | 34.770<br>(3.622)***   | 103.945<br>(12.221)*** | 26.059<br>(2.579)***   | 100.803<br>(7.831)***  | 34.451<br>( 2.702)***  | 126.451<br>(4.495)***  |
| AR(1)             | 0.987<br>(0.015)***    | 1.411<br>(0.009)***    | 0.990<br>(0.005)***    | 0.983<br>(0.011)***    | 0.988<br>(0.005)***    | 1.346<br>(0.017)***    |
| AR(2)             |                        | -0.419<br>(0.008)***   |                        |                        |                        | -0.356<br>(0.005)***   |
| MA(1)             | -0.703                 | -0.762                 | -0.598                 | -0.660                 | -0.659                 | -0.930                 |

|                | Narela            |                  | Okhla             |                  | Pusa              |                  |
|----------------|-------------------|------------------|-------------------|------------------|-------------------|------------------|
|                | PM <sub>2.5</sub> | PM <sub>10</sub> | PM <sub>2.5</sub> | PM <sub>10</sub> | PM <sub>2.5</sub> | PM <sub>10</sub> |
| MA(2)          | (0.057)***        | (0.045)***       | (0.013)***        | (0.032)***       | (0.018)***        | (0.052)***       |
|                | -0.236            | -0.125           | -0.323            | -0.276           | -0.266            |                  |
|                | (0.024)***        | (0.022)***       | (0.014)***        | (0.016)***       | (0.018)***        |                  |
| <i>d</i>       | 0.459             | 0.147            | 0.386             | 0.485            | 0.415             | 0.391            |
|                | (0.131)***        | (0.042)***       | (0.029)***        | (0.055)***       | (0.032)***        | (0.039)***       |
| Variance Model |                   |                  |                   |                  |                   |                  |
| Constant       | 12.430            | 46.669           | 17.645            | 73.193           | 14.947            | 62.191           |
|                | (4.407)***        | (21.206)**       | (4.937)***        | (27.636)***      | (4.476)***        | (21.912)***      |
| $\alpha_1$     | 0.147             | 0.108            | 0.205             | 0.161            | 0.211             | 0.145            |
|                | (0.021)***        | (0.018)***       | (0.029)***        | (0.027)***       | (0.033)***        | (0.028)***       |
| $\beta_1$      | 0.852             | 0.891            | 0.794             | 0.838            | 0.788             | 0.853            |
|                | (0.019)***        | (0.017)***       | (0.025)***        | (0.023)***       | (0.028)***        | (0.023)***       |

\*\*\* $p < 0.01$ , \*\* $p < 0.05$ , \* $p < 0.10$ ; S.E. is in parenthesis

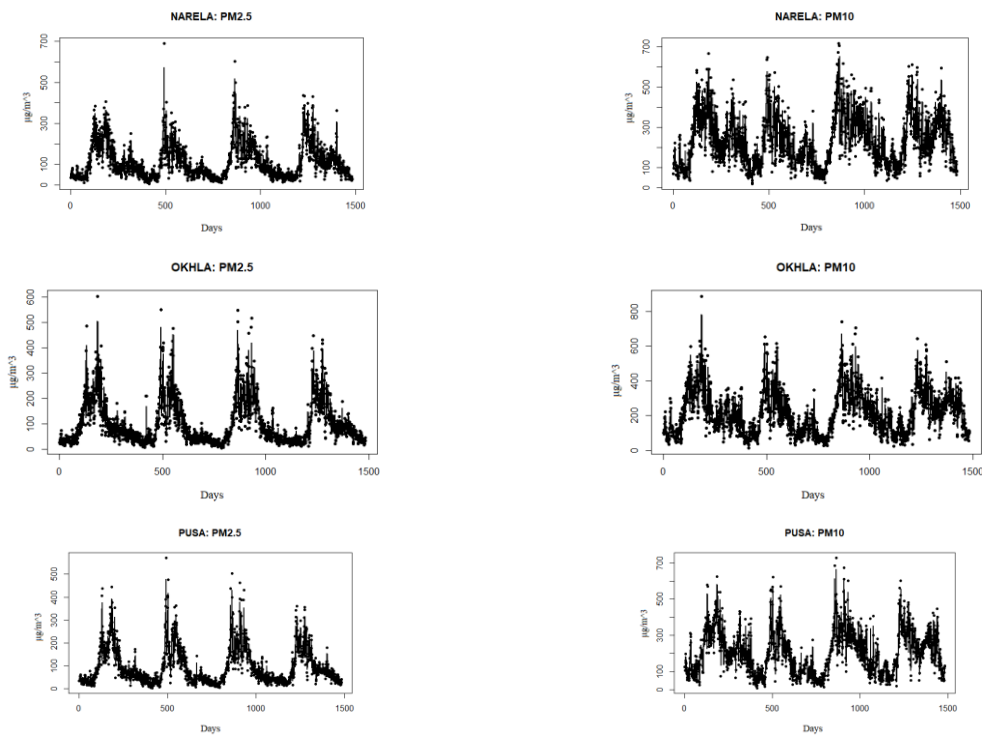


Fig. 4. Observed (marker) vs. fitted (line) of the selected series

Table 5. Forecasting performance of fitted models in model validation set

| Site   | Model  | RMSE   | MAE    | MAPE (%) |
|--------|--|--------|--------|----------|
| Narela | PM <sub>2.5</sub> ARFIMA (1, <i>d</i> ,2) -GARCH (1,1) | 15.411 | 14.045 | 8.268    |
|        | PM <sub>10</sub> ARFIMA (2, <i>d</i> ,2) -GARCH(1,1)   | 40.290 | 35.496 | 6.779    |
| Okhla  | PM <sub>2.5</sub> ARFIMA (1, <i>d</i> ,2) -GARCH (1,1) | 16.834 | 16.045 | 8.639    |
|        | PM <sub>10</sub> ARFIMA (1, <i>d</i> ,2) -GARCH (1,1)  | 41.775 | 39.029 | 6.428    |
| Pusa   | PM <sub>2.5</sub> ARFIMA (1, <i>d</i> ,2) -GARCH (1,1) | 14.677 | 14.128 | 7.928    |
|        | PM <sub>10</sub> ARFIMA (2, <i>d</i> ,1) -GARCH (1,1)  | 50.594 | 44.329 | 8.773    |

#### 4. CONCLUSION

In this paper, an attempt has been made to model the variation of PM<sub>2.5</sub> and PM<sub>10</sub> concentration for three selected location in Delhi.

Due to the presence of long memory in mean structure, the ARFIMA model is applied as the mean model and the GARCH model as the variance model. Modeling can be helpful for understanding the fluctuation of concentrate of



these two pollutants. Apart from the year-round measures already in place, the peak period of air pollution in Delhi, from late-October to early-January, demands special attention of policymakers. Few of the proactive measures that can substantially alleviate the PM-pollution are banning the burning of stubbles and firecrackers, installation of smog towers, and being more stringent about vehicular emissions.

## COMPETING INTERESTS

Authors have declared that no competing interests exist.

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