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Spatio-temporal Variation of Meteorological Influence on $PM_{2.5}$ and PM_{10} over Major Urban Cities of Bangladesh

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ABSTRACT

A detrended seasonal analysis on a 6-year (2013–2018) dataset of daily Particulate Matter (PM) concentration and meteorological parameters is performed to understand the spatio-temporal variation of PM and the seasonal influence of meteorological factors on PM pollution over 6 major urban cities of Bangladesh. Cross-correlation and multiple non-linear regression (MNLR) of air quality and meteorological data were used to explore the meteorology-PM interactions and their spatio-temporal variability. Meteorological influence on PM was found to be stronger in the southern part of the country relative to the northwestern part. MNLR analysis implied that meteorological parameters could explain up to 39% of daily PM variability during high pollution days. The deposition effect of relative humidity was prominent during the premonsoon season, while rainfall impact becomes dominant in the monsoon season, specifically in the northeastern region. Wind speed was observed to have a dilatory effect on PM variation, although wind seemed to carry sea aerosol in southern regions. In addition, the northwestern wind appeared to contribute to PM rise in most urban areas by carrying PM loading. In winter, the low temperature was found to favor PM accumulation, while in monsoon, high temperature causes PM rise, possibly by assisting atmospheric secondary aerosol formation. Solar radiation positively influenced atmospheric PM formation, and the influence was stronger in the northwestern region. It is shown that meteorological parameters influence the seasonal variability of PM, but the extent of this influence varies depending on temporal and regional factors.

Keywords: Particulate matter, Meteorology, Seasonal variation, Cross-correlation, Multiple non-linear regression

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1 INTRODUCTION

Air pollution in major cities of Bangladesh has become quite acute in recent years due to rapid industrialization and urbanization. Dhaka, the capital of Bangladesh, was ranked as the 2nd most polluted city globally in 2019 (AirVisual, 2019). Besides, Gazipur and Barisal—two other major cities of Bangladesh—were ranked as the 38th and 41st most polluted cities globally in 2018 (CBS News, 2019). Road and building construction activities to support urbanization, mushrooming of brick kilns to facilitate construction, increased traffic and resulting vehicular emissions, and ongoing infrastructure megaprojects are responsible for exacerbating the air quality in urban areas of Bangladesh. Among all air pollutants, particulate matter ($PM_{2.5}$ and PM_{10}) is considered one of the most harmful elements due to its link with human health. Because of its size, PM can enter the bloodstreams of respiratory tracts, causing respiratory diseases and even death (WHO, 2016). It also affects visibility and is responsible for global and regional climate change (Won *et al.*, 2021).

Since PM is a crucial factor in air quality degradation, it has become an important research topic for the scientific community (Mahapatra *et al.*, 2018; Li *et al.*, 2017a; Munir *et al.*, 2013). Many studies have been performed to understand the physical, chemical, and optical properties of PM and to explore the driving factors influencing the spatial variability of PM (Islam *et al.*, 2022b; Hajiloo *et al.*, 2019; Mancilla *et al.*, 2015; Ganguly *et al.*, 2006). Meteorology has been found to be one of the primary determinants of PM variation in the atmosphere (Liu and Cui, 2014; Trivedi *et al.*, 2014). Studies have shown that meteorological parameters such as wind speed, temperature, relative humidity, solar radiation, rainfall, atmospheric boundary layer, pressure system play a significant role in explaining PM variation in the USA, China, and India (Islam *et al.*, 2022a; Singh *et al.*, 2021; Ilias *et al.*, 2020; Wang *et al.*, 2013). Hassan *et al.* (2020) investigated the long-term PM relationship with meteorological parameters in Malaysia and identified that PM is strongly correlated with temperature, precipitation, and relative humidity. Mahapatra *et al.* (2018) examined a three-year dataset of PM and meteorology and observed that local meteorology and long-range transport significantly contribute to aerosol particle variation in eastern India. Chen *et al.* (2018) proposed a non-linear lag-response model for predicting $PM_{2.5}$ using meteorological information in China. Li *et al.* (2017b) reviewed major advances in aerosol-boundary layer interaction processes and stated that planetary boundary layer plays a vital role for aerosol accumulation in the atmosphere. In addition, studies have found that wind shear, temperature inversion, and long-range transport are physically relevant to the variation of PM concentration (Bai *et al.*, 2022; Braun *et al.*, 2020; Guo *et al.*, 2020; Zhang *et al.*, 2020; Xu *et al.*, 2019; Guo *et al.*, 2017; Wu *et al.*, 2014). Available literature corroborates the need for understanding meteorology to comprehend the spatio-temporal variability of PM.

Since the pattern of atmospheric circulation and corresponding pressure systems vary regionally, the atmospheric influence on PM is likely to vary from region to region (Chen *et al.*, 2020). Li *et al.* (2019) observed that the meteorological influence on PM was different in different regions of China. Azmi *et al.* (2010) stated that the variation of PM_{10} might be attributed to regional tropical factors in Malaysia. Therefore, region-based study is necessary to understand a comprehensive meteorology-PM relationship for a certain area. As for Bangladesh, studies investigating the meteorology-PM interaction mostly focused Dhaka city. For example, Islam *et al.* (2015, 2022d) explored the meteorological influence on PM in Dhaka. Afrin *et al.* (2021) developed a meteorology-based PM prediction model and it was for Dhaka city too. Although some studies explored the air pollution scenario of other major cities of Bangladesh, meteorological impacts on air quality were not assessed. For example, Rahman *et al.* (2019) investigated the intra-site and inter-site air pollutant correlations between Dhaka, Gazipur and Narayanganj city. Shahriar *et al.* (2020) determined the efficacy of several machine learning algorithms to predict air pollutants in the city of Dhaka, Chittagong, Sylhet, and Rajshahi. However, as mentioned earlier, the impact of meteorological parameters (wind speed, temperature, relative humidity etc.) on air quality was not investigated at those cities. A recent study attempted to determine the correlation between meteorology and PM at six major cities of Bangladesh using back trajectory and conditional probability function analysis (Rana and Khan, 2020). However, the time dependent non-linear relationship of meteorology and PM was not explored here. Thus, the spatial and temporal variability of PM in Bangladesh and its interaction with meteorology is still poorly constrained.

We performed annual and seasonal cross-correlation analysis of meteorological parameters and PM concentrations—measured in eight monitoring stations of Bangladesh—to accomplish three objectives: (a) present spatio-temporal variability of PM pollution in Bangladesh, (b) assess the seasonality in meteorological influences on PM, and (c) compare the meteorological influences on PM among 5 major urban cities of Bangladesh. In the cross-correlation analysis, we also explored the relationship between wind azimuths and PM and observed their relationship for different regions. In addition, we performed seasonal multiple non-linear regression analysis to assess the temporal meteorological impact on PM variation in different regions. In this analysis, we incorporated the lagged terms of meteorological parameters which, from cross-correlation analysis,

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was noted to have strong influence on PM variation. We also considered the interaction terms of meteorological parameters to assess their internal association in affecting the PM variation. Finally, we validate our regression analysis by applying them for a recent dataset in one of the monitoring stations.

2 METHODS

2.1 Study Area

This study encompasses five out of eight divisions (main administrative units) and six major cities (within the divisions) of Bangladesh. Air quality and meteorological data of these cities were collected from the Continuous Air Monitoring Stations (CAMSs) in those cities. There are eleven CAMSs in Bangladesh where real-time monitoring of PM concentration and meteorological parameters is performed. PM concentration is monitored using the beta attenuation method (Model BAM-1020) by Met One Instrument Inc., USA. Due to poor quality data, three CAMS were discarded from our analysis. The remaining eight stations—located in six cities, as mentioned above—were the data source of this study. The location of these stations is presented in Fig. 1, and the details are provided in Table S1.

2.2 Climatology of Bangladesh

Bangladesh has four seasons with marked seasonal variation: Winter (December–February), Premonsoon (March–May), Monsoon (June–September), and Post-monsoon (October–November). During winter, cold-dry calm wind (0–2 m s^{-1}) from the northwestern direction prevails over the country. However, the direction of wind flow is southwesterly in the hilly eastern region. Low humidity, rainfall, temperature, and solar radiation persist in this season. After winter, premonsoon comes. In this season, wind flows at a maximum speed ranging from 2 to 4 m s^{-1} and has variable

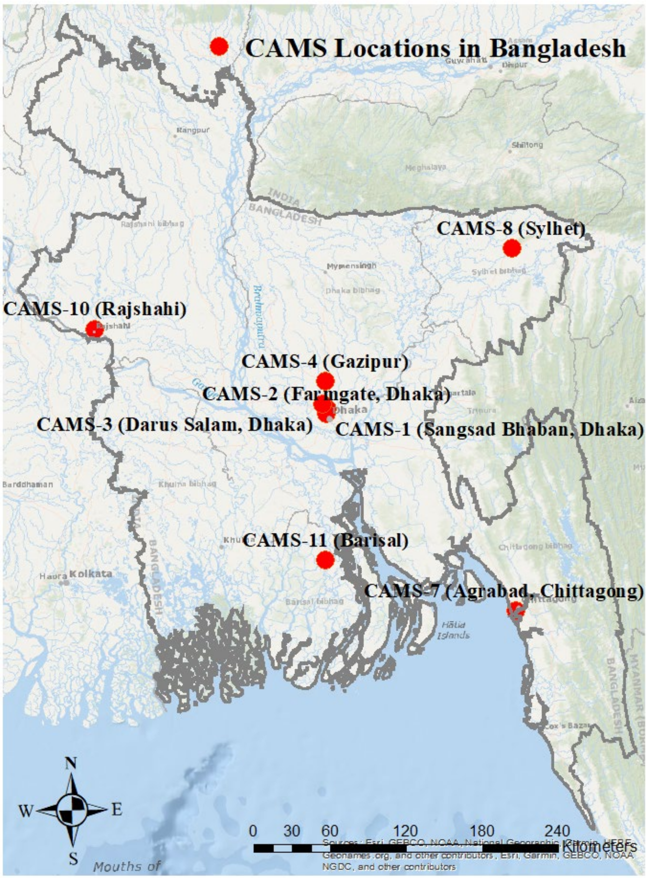

Fig. 1. Location of CAMSs in major urban cities of Bangladesh.

directions. This season is characterized by the hottest weather and thunderstorms, which are called Norwesters. These short-span thunderstorm events occur from April to May and shower this territory with gusty wind and torrential rain. Besides, temperature, radiation, humidity, and rainfall start to increase during this season. After the premonsoon, monsoon comes. During monsoon, moist warm high-speed wind (3–4 m s^{-1}) flows from the southwestern direction. This season is characterized by high humidity and persistent rainfall. After monsoon, postmonsoon arrives. In this season, precipitation, humidity, temperature, radiation, and wind speed start to decrease. After postmonsoon, winter comes again. A summary statistic of the meteorological parameters—categorized by seasons—in each CAMS is reported in Table S2, and the wind rose diagrams are shown in Fig. S2.

2.3 Data Pre-processing and Filtering

The raw dataset contained a significant number of outliers and missing values. Dataset was pre-processed through outlier removal (using the iterative method) and missing value imputation (using the '*k*-NN' algorithm). The dataset is filtered by the Kalman Filter algorithm, which is implemented in PyCharm Community Edition, version 2020.2.3. The processes are described in detail in Supplementary Materials.

2.4 Data Structure and Cross-correlation Analysis

The data being analyzed contained eight linear variables—$PM_{2.5}$, PM_{10}, wind speed, temperature, relative humidity, solar radiation, rainfall amount and duration, and one angular variable—wind direction. Wind direction—measured clockwise from the geographical north and expressed in degrees—was converted to trigonometric cosine and sine of wind azimuths, representing the north-south and east-west components, respectively. Finally, cross-correlation analysis was performed on the filtered time-series data (discussed in Section 2.3 and Section S2 of the Supplementary Material) of PM concentration ($PM_{2.5}$ and PM_{10}) and meteorological parameters (wind speed, cosine and sine component of wind speed, temperature, relative humidity, solar radiation, rainfall amount and duration). The basic cross-correlation formula is presented in Eq. (1) and Eq. (2).

$$\text{when } k \geq 0,\ C_{xy}(k) = \sum_{t=1}^{T-k} \frac{1}{T}\left[x(t) - \bar{x}\right]\left[y(t+k) - \bar{y}\right] \tag{1}$$

$$\text{when } k < 0,\ C_{xy}(k) = \sum_{t=1}^{T-k} \frac{1}{T}\left[y(t) - \bar{y}\right]\left[x(t-k) - \bar{x}\right] \tag{2}$$

Here, $C_{xy}(k)$ is the cross-correlation function, $x(t)$ was concerned meteorological parameter at time t, $y(t + k)$ was PM concentration at time $(t + k)$, k was lag between meteorological parameter and PM concentration, and T was the length of data-series. The cross-correlation coefficient was determined using Eq. (3) from the cross-correlation function:

$$r_{xy}(k) = \frac{c_{xy}(k)}{S_x S_y} \tag{3}$$

Here, $S_x = \sqrt{C_{xx}(0)}$ and $S_y = \sqrt{C_{yy}(0)}$. If the cross-correlation coefficient r_{xy} is positive, PM and meteorological parameters vary proportionally, and vice versa. If lag k is positive, meteorological parameters lead PM and vice versa.

2.5 Multiple Non-linear Regression (MNLR)

We used multiple non-linear regression (MNLR) to determine the influence of combined meteorological parameters on PM variation. The model used Log-transformed PM time series (as the dependent variable) because PM concentration had been mathematically shown to have log-normal distribution (Ott, 1990). Many studies—investigating indoor (Islam *et al.*, 2022c; Young *et al.*, 2019) and outdoor PM concentrations (Beckerman *et al.*, 2013) and PM emissions (Islam *et al.*, 2021)—found the same and used logarithmic PM distribution in models/analyses. In our dataset, the logarithm of daily PM concentration follows normal distribution determined by Kolmogorov-Smirnov test (p = 0.0049 and 0.0710 for $PM_{2.5}$ and log($PM_{2.5}$), respectively and p = 0.0035 and 0.0821 for PM_{10} and log(PM_{10}), respectively). Therefore, our approach to selecting the logarithmic regression model aligns with the previous findings. Studies have also shown that transforming PM to logarithmic distribution helps reduce skewness and, in this way, helps in improving accuracy (Song *et al.*, 2014; Tian and Chen, 2010; Liu *et al.*, 2007). In MNLR models, the significance of independent variables was assessed at a 99% confidence level. We explored three approaches to develop regression models for each season. As the first approach, each meteorological parameter was added as an independent variable along with the lead or lagged terms—obtained from the seasonal cross-correlation analysis. Next, non-linear regression (up to two degrees) was incorporated (2nd approach). Finally, interaction terms of the independent variables (i.e., meteorological parameters) were added (3rd approach). The model/approach with the lowest PRESS and highest adjusted r^2 value (discussed below) was selected for each case.

The general form of the MNLR model used is presented in Eq. (4).

$$\log y = \beta_0 + \sum_{k=1}^{n} \beta_k x_{1_k} + \sum_{k=1}^{n} \beta_k {x_1}^2{}_k + \sum_{k=1}^{n} \beta_k x_1 x_{2_k} + \varepsilon \tag{4}$$

Here, n was the number of meteorological parameters (n = 1–8), y was PM concentration, x_1 and x_2 both were meteorological parameters, x_1x_2 was the interaction term of meteorological parameters, β was regression coefficient, and ε was error term, where $\varepsilon = (y_i - \hat{y})$, y_i = observed y values and $\hat{y}$ = y values given by Eq. (4). The coefficient of determination (r^2) measured the extent of meteorological influence on PM variation, determined by Eq. (5).

$$r^2 = \frac{St - Sr}{St} \tag{5}$$

Here, St and Sr represented the total sum of squares ($\sum_{i=1}^{n}(y_i - \bar{y})^2$) and error sum of squares $\sum_{i=1}^{n}(y_i - \hat{y})^2$, respectively. However, r^2 might reduce the regression efficiency by increasing its values with increasing terms to the model. Hence, r^2 was adjusted based on the added terms, determined using Eq. (6).

$$Adjusted\ r^2 = 1 - (1 - r^2)\frac{m-1}{m-n-1} \tag{6}$$

Here, m was the element number in a series, and n was the total number of considered meteorological parameters. We also used Prediction Error Sum of Squares (PRESS) to assess the efficacy of regression by detecting the presence of any excess independent variable. A smaller PRESS value indicates better efficacy of the regression analysis, which was determined by Eq. (7).

$$PRESS = \sum_{i}^{T} \frac{(y_i - \hat{y})^2}{(1 - h_{ii})^2} \tag{7}$$

Here, h_{ii} was i^{th} 'Leverage Value,' which only relied on the meteorological parameters. For n = 2 and sample size of T,

$$h_{ii} = \frac{1}{T} + \frac{\left(x_i - \bar{x}\right)^2}{\sum_{j=1}^{n}\left(x_j - \bar{x}\right)^2} \tag{8}$$

3 RESULTS AND DISCUSSION

3.1 Annual Trend

The annual average concentration of $PM_{2.5}$ and PM_{10} over eight stations for the period of 2013–2018 is shown in Fig. 2. Here, it can be observed that the PM concentration of all stations exceeds the annual Bangladesh National Ambient Air Quality Standard (Hossen and Hoque, 2018). Among all stations, the highest PM concentration is observed at Darus Salam, Dhaka. In general, PM levels started decreasing in 2014, then started rising again in 2017. A similar trend is observed for other stations located in Dhaka, Gazipur, and Chittagong. This may be explained by the enactment of the Brick Kiln Control Act 2013 at the end of 2014 (DoE, 2017), after which the emission control activities (punitive actions by the Department of Environment) increased. However, PM concentration shows a sharp rise in 2018, when the 11^{th} National Parliament Election was held (The Daily Star, 2018). Before the election, construction activities of some mega projects were accelerated, namely, Dhaka Metro Rail Project, Dhaka-Gazipur Four Lane Expressway Project and Improvement of Agrabad Access Road Project in Chittagong (Islam, 2018). As part of these construction works, brick kiln operation increased, which, in combination with construction works, possibly led to the rise in PM concentrations in 2018. In addition to interannual trend analysis, the spatial variability of seasonal average PM concentration is also investigated. From the seasonal spatial distribution maps of $PM_{2.5}$ and PM_{10} (Fig. S3 and Fig. S4), it can be observed that $PM_{2.5}$ concentration remains high to moderate in the central to southern region and low in the northern region of Bangladesh. However, PM_{10} concentration remains high in the northwestern and central region of Bangladesh. Northwestern region is the entrance point of long-range transported pollutants in Bangladesh (Begum *et al.*, 2016), and high PM_{10} is observed here.

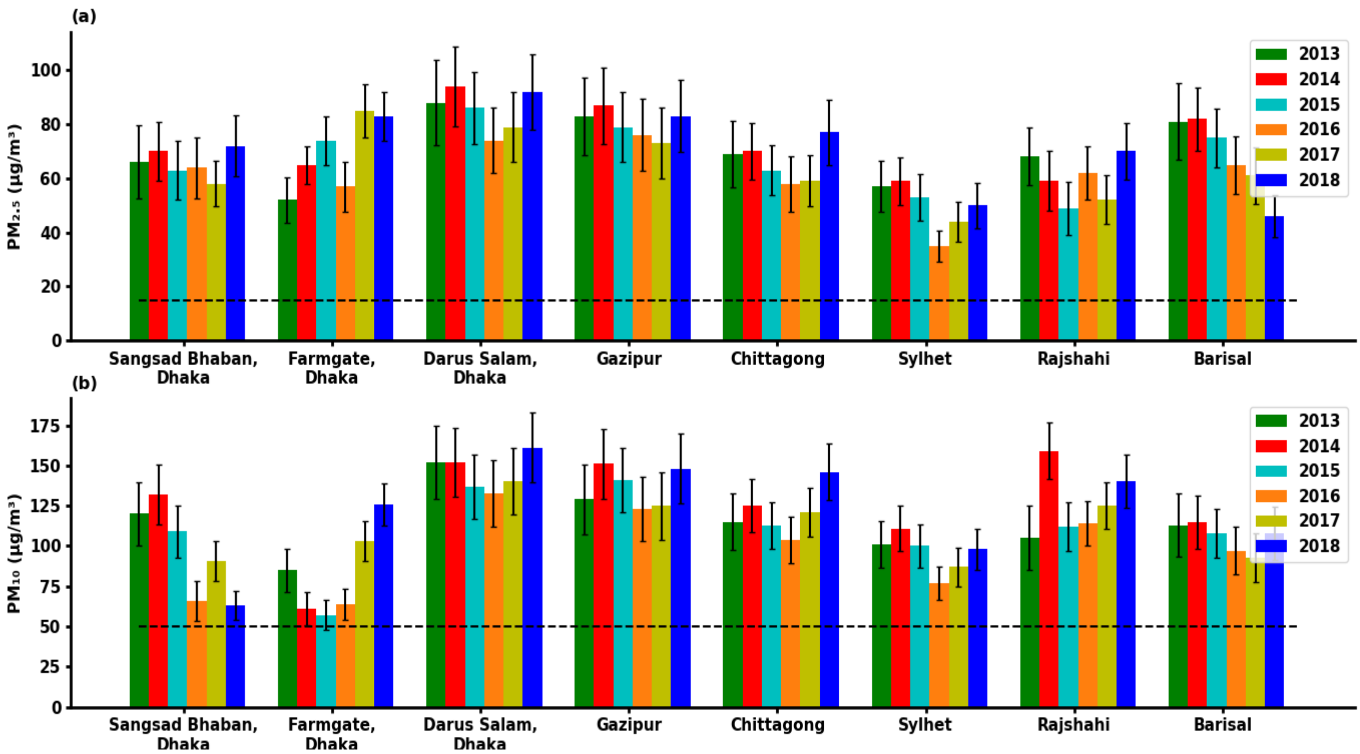

Fig. 2. The annual average concentration of (a) $PM_{2.5}$ and (b) PM_{10}. Here, error bars indicate 95% confidence interval. The black dashed lines represent the Annual Bangladesh National Ambient Air Quality Standard of $PM_{2.5}$ (15 µg m^{-3}) and PM_{10} (50 µg m^{-3}).

3.2 Annual Cross-correlation Between PM and Meteorology

Annual cross-correlation analysis is performed between the daily dataset of PM and meteorological parameters from 2013–2018, and the summary is presented in Table 1. Here, wind speed, relative humidity, and rainfall show negative, and solar radiation shows a positive correlation with PM. Temperature shows both positive and negative correlations with PM depending on stations (Table 1). A negative correlation between most of the meteorological parameters and PM implies that an increase in those meteorological parameters will cause a decrease in PM and vice versa. In addition, Table 1 shows that the meteorological parameters show correlation with PM within 0–3 days lag (enclosed in parenthesis). This lag value represents the tentative time taken by the meteorological parameters to exert noticeable influence on PM. Zero (0) lag means, the concerned meteorological parameter of a specific day is related to the PM concentration of the same day. Positive lag (such as, +1) means the meteorological parameter of a specific day is related to the PM concentration of the following (one day later) day. Negative lag (such as, –1) means meteorological parameter of a specific day is related to the PM concentration of the previous (one day earlier) day. Therefore, positive lag means meteorological parameter leads PM, negative lag means PM leads meteorological parameter and '0' lag means simultaneous interaction.

3.2.1 Wind speed and direction

Among all the meteorological parameters, wind speed shows the highest negative correlation with PM fractions for all stations (Table 1). A negative correlation between wind speed and PM implies that high wind speed favors PM dissipation and low wind speed favors PM accumulation. In all stations except Sangsad Bhaban and Barisal, $PM_{2.5}$ shows a higher negative correlation with wind speed than PM_{10}. High wind speed, in addition to PM dissipation, can sometimes cause an increase in PM_{10} by resuspending road dust, leading to a weaker negative correlation with PM_{10} than $PM_{2.5}$ (Elminir, 2005; Jung *et al.*, 2002). However, in Sangsad Bhaban and Barisal, the correlation of wind speed is higher with PM_{10} than $PM_{2.5}$. In Sangsad Bhaban premises, traffic emission is low, and the station is installed over 100 m away from nearby traffic road. Moreover, high grass cover exists in Sangsad Bhaban premises, making the road dust resuspension minimal due to increased friction (Li *et al.*, 2017a; Hamed *et al.*, 2011). In Barisal, a major $PM_{2.5}$ pollution source is the water

Table 1. Annual cross-correlation coefficients between meteorological parameters and PM over eight stations showing maximum correlation coefficients and corresponding lag period in days (in parenthesis).

	WS	T	RH	SR	R	RD
$PM_{2.5}$						
CAMS-1(Sangsad Bhaban, Dhaka)	**–0.211(0)****	**–0.140(1)****	**–0.142(0)****	0.016(0)	–0.050(0)	–0.063(0)
CAMS-2 (Farmgate, Dhaka)	**–0.171(0)****	–0.050(0)	**–0.100(0)****	0.050(0)	–0.030(0)	–0.034(0)
CAMS-3 (Darus Salam, Dhaka)	**–0.376(0)****	**–0.126(3)****	**–0.149(0)****	0.070(3)	–0.053(0)	–0.060(0)
CAMS-4 (Gazipur)	**–0.364(0)****	**–0.140(3)****	**–0.162(1)****	**0.084(0)***	–0.063(0)	–0.076(0)
CAMS-7 (Agrabad, Chittagong)	**–0.316(0)****	**–0.095(2)****	**–0.117(0)****	0.071(1)	–0.045(0)	–0.042(0)
CAMS-8 (Sylhet)	**–0.263(0)****	**–0.102(3)****	**–0.076(0)***	0.050(1)	**–0.132(0)****	**–0.158(0)****
CAMS-10 (Rajshahi)	**–0.135(0)****	**–0.120(2)****	–0.033(0)	**0.108(1)****	–0.001(0)	–0.003(0)
CAMS-11 (Barisal)	**–0.274(0)****	**–0.124(2)****	**–0.197(0)****	**0.088(1)****	–0.028(0)	–0.051(0)
PM_{10}						
CAMS-1(Sangsad Bhaban, Dhaka)	**–0.248(0)****	**–0.110(2)****	**–0.207(0)****	**0.071(0)****	**–0.195(0)****	**–0.253(0)****
CAMS-2 (Farmgate, Dhaka)	**–0.155(0)****	0.023(0)	**–0.080(0)***	0.023(0)	–0.000(0)	–0.056(0)
CAMS-3 (Darus Salam, Dhaka)	**–0.318(0)****	**–0.111(3)****	**–0.288(0)****	**0.131(1)****	**–0.087(0)***	**–0.108(0)****
CAMS-4 (Gazipur)	**–0.362(0)****	**–0.157(3)****	**–0.290(0)****	**0.158(0)****	**–0.102(0)****	**–0.123(0)****
CAMS-7 (Agrabad, Chittagong)	**–0.272(0)****	**0.100(0)****	**–0.328(0)****	**0.165(0)****	**–0.101(0)****	**–0.107(0)****
CAMS-8 (Sylhet)	**–0.247(0)****	**0.170(0)****	**–0.194(0)****	**0.135(0)****	**–0.214(0)****	**–0.244(0)****
CAMS-10 (Rajshahi)	**–0.101(0)****	**–0.102(3)****	–0.136(0)**	**0.186(0)****	**–0.112(0)****	**–0.125(0)****
CAMS-11 (Barisal)	**–0.302(0)****	**–0.133(3)****	**–0.368(0)****	**0.143(0)****	–0.076(0)	**–0.107(0)****

Statistical significance indicators are as follows: ** $p < 0.0001$; * $0.001 > p > 0.0001$, otherwise $0.01 > p > 0.001$. Here, WS = Wind Speed, WD = Wind Direction, T = Temperature, RH = Relative Humidity, SR = Solar Radiation, R = Rainfall Amount, RD = Rainfall Duration.

vessel emissions in the nearby Kirtonkhola river port (Rana and Khan, 2020; Cheng and Li, 2010). Irrespective of the magnitude of wind speed, the contribution of river vessels to $PM_{2.5}$ emission remains consistent throughout the year, resulting in a lower negative correlation between wind speed and $PM_{2.5}$. For the same reason, $PM_{2.5}$ is less dependent on other meteorological parameters compared to PM_{10} in Barisal. The negative correlation between PM_{10} and wind speed is lowest in Rajshahi, which is located in the northwestern part of Bangladesh. Here, the wind comes from the continental regions of the Arabian Peninsula, which is characterized by haze (Begum *et al.*, 2016). This transboundary airflow contains natural dust, which primarily consists of coarser-sized particles (PM_{10}) (Fuzzi *et al.*, 2015). This transboundary pollution might result in a lower negative correlation between wind speed and PM_{10} in Rajshahi.

The annual cross-correlation coefficients between wind direction and PM are presented in Table S3 of supplementary materials. Table S3 shows that the cosine and sine components of wind speed show positive and negative correlations with PM, respectively, for majority of stations. Positive cosine values are associated with the wind coming from the 270°–0°–90° directions, and negative sine values are associated with the wind from the 180°–270°–360° directions. Therefore, the correlation pattern may imply that the airmass contains higher PM loading when it comes from the northwestern direction. However, the cosine and sine components of wind azimuths are negatively correlated with PM in Sylhet (Table S3). Such correlation may infer that PM loading remains high in the southwestern wind here. For the majority of stations, the components of wind speed show higher correlations with PM_{10} relative to $PM_{2.5}$, suggesting that in addition to local sources, a significant contribution of PM_{10} comes from long-range transportation.

3.2.2 Temperature

Temperature shows a negative correlation with PM for most stations (Table 1). This may refer to the PM dilution event caused by the increase in boundary layer height preceded by ambient temperature rise. However, in high vegetative areas, such as Sylhet and Chittagong, a positive correlation is observed between PM_{10} and temperature. In such areas, non-volatile organic compound (NVOC) is one of the major sources of atmospheric particles (Holmes, 2007). Since, NVOC emission is largely modulated by temperature (Kim *et al.*, 2020), temperature increase might eventually lead to coarser sized particle increase in the atmosphere.

3.2.3 Relative humidity and rainfall

Relative humidity, rainfall amount, and rainfall duration show a negative correlation with PM for all stations, which may represent wet deposition, flocculation, and subsequent gravitational settling of PM. For most stations, the correlation of relative humidity and PM is stronger than that of rainfall properties (amount and duration) and PM. Since, in these areas, precipitation events are irregular, the effect of rainfall is not that much prominent on PM. However, in Sylhet, rainfall exerts the strongest negative correlation with PM. Since the rainfall events are heavy and consistent in Sylhet, the scrubbing effect of precipitation is predominant here. Rainfall duration is found to have a higher negative correlation with PM than rainfall amount for all stations, indicating that consistency of rainfall has a more reducing impact on PM than that of rainfall intensity. Therefore, we used only the rainfall duration parameter to represent rainfall property in our subsequent analysis.

3.2.4 Solar radiation

Solar radiation correlates positively with PM fractions, and the correlation is stronger for coarser particles (PM_{10}). This may refer to the fact that, solar radiation induces photochemical reactions which propitiate the daytime O_3, sulfate particles and secondary organic aerosol formation through oxidation process. The enhanced secondary aerosol production and condensation of atmospheric sulfuric acid can combinedly contribute to new particle formation (Wang *et al.*, 2016). Literature showed that solar radiation is the driving factor to produce new particles in the atmosphere by catalyzing photochemical reactions of various pre-existing ions with OH^- radical. In the presence of high-temperature conditions, these photochemical reactions get boosted up (Wonaschütz *et al.*, 2015; Hamed *et al.*, 2011; Vehkamaki *et al.*, 2004). Under a moist atmosphere, these new particles instantly undergo hygroscopic growth and become coarser in size (Seinfeld and

Pandis, 2016). Therefore, under the combination of high solar radiation, temperature, and relative humidity, the secondary formation and growth of coarser particles increases. This phenomenon might lead to a high positive correlation between PM_{10} and solar radiation. Nonetheless, the highest positive correlation between solar radiation and PM is observed in Rajshahi. Here, the extent of the sunshine hour and incident solar radiation is maximum (Datta *et al.*, 2014), resulting in a strong positive correlation between PM and solar radiation.

3.3 Aerosol-meteorology Interaction

In order to understand how PM and meteorological variables vary over time, a summary statistic of PM and meteorological variables for different seasons is presented in Table S2 of supplementary materials. From Table S2, it is evident that PM level is the highest during winter, the lowest during monsoon and moderate during premonsoon and postmonsoon seasons. We investigated how this PM variation can be attributed to meteorological influences through seasonal cross-correlation analysis and presented the seasonal cross-correlation coefficients between PM and meteorological parameters in Table 2 and Table 3, where the lag periods are shown in days within parenthesis. These tables implicate the seasonal influence and lag effect of meteorological parameters on PM concentration.

3.3.1 Wind speed

A strong negative correlation between wind speed and PM is observed during winter and monsoon season (Table 2 and Table 3). The calm wind of winter and the high-speed wind of monsoon might influence such a correlation (Jacobson and Kaufman, 2006). However, in Chittagong, the lowest negative correlation between PM_{10} and wind speed is observed in monsoon. Since Chittagong is a coastal city, here inflow of sea-aerosol by high-speed monsoon wind is very prominent. During premonsoon, the occurrence of Norwester (a thunderstorm event) is prevalent, which kicks up the soil particles causing resuspension of PM_{10}. Hence, a lower negative correlation between premonsoon PM_{10} and wind speed is observed. Additionally, the negative correlation between premonsoon PM_{10} and wind speed is noticeably low in Barisal. Barisal is in the southern part of the country, and it encounters the strongest surge of Norwester every year, leading to more frequent dust resuspension. This phenomenon might result in the poor negative correlation between premonsoon PM_{10} and wind speed in Barisal. The highest negative correlation between wind speed and PM ($PM_{2.5}$ and PM_{10}) is observed in Darus Salam, Dhaka and Gazipur, which are the zones of highest PM pollution. It suggests that PM variation is strongly modulated by wind speed in regions with higher pollution levels.

In order to understand the influence of wind direction on high PM loading, wind rose diagrams for eight stations of Bangladesh are plotted for the winter season in Fig. S2. It shows that wind flow from the north-westerly direction affects PM variation in the majority of stations in winter. In addition to wind rose diagrams, seasonal cross-correlation coefficients between wind direction and PM are also determined and presented in Table S4 of supplementary materials. Table S4 shows that, in addition to the northwestern wind, high PM loading of Gazipur and Barisal are also associated with the northeastern wind direction in winter (Table S4). The long-range transport of pollution in Gazipur may play a role in this regard. Gazipur is observed to have PM contribution from the eastern state of Tripura and the northeastern state of Assam/Meghalaya of India (Rana *et al.*, 2016). Therefore, when the winter wind blows from these directions, it brings airmass high in PM loading to Gazipur. In contrast, in Barisal, primary pollution sources are local and are in the northern direction of Barisal station. As a result, the wind might influence PM variation from this direction. In Sylhet, where the southwestern wind is prevalent in winter, a moderate correlation between the southwestern wind component and $PM_{2.5}$ is observed (Table S4). The predominant southwesterly wind conveys air from Dhaka-Gazipur and thus contributes to PM loading in the urban air of Sylhet.

3.3.2 Temperature

Temperature and PM are negatively correlated during winter and positively correlated during other seasons, as shown in Table 2 and Table 3. Here, it can be observed that the negative correlation is stronger for $PM_{2.5}$ than PM_{10}. This trend can be explained by the phenomena of

Table 2. Seasonal cross-correlation coefficients between meteorological parameters and $PM_{2.5}$ over eight stations showing maximum correlation coefficients and corresponding lag period in days (in parenthesis).

	WS	T	RH	SR	RD
CAMS-1 (Sangsad Bhaban, Dhaka)					
Winter	**–0.284(0)****	**–0.249(1)****	**–0.156(1)****	**0.168(2)****	**–0.184(0)****
Premonsoon	**–0.251(0)****	0.003(0)	**–0.190(0)****	0.041(0)	–0.002(0)
Monsoon	**–0.185(0)****	0.028(0)	–0.101(0)	**0.113(0)**	0.004(0)
Postmonsoon	**–0.177(0)***	–0.096(–2)	**–0.178(0)****	**0.103(0)**	0.044(0)
CAMS-2 (Farmgate, Dhaka)					
Winter	**–0.160(0)****	0.023(0)	–0.027(0)	0.063(0)	0.048(0)
Premonsoon	**–0.252(0)**	–0.056(0)	**–0.140(0)****	0.034(0)	**–0.100(0)**
Monsoon	**–0.148(0)****	0.114(7)	**–0.115(0)****	0.030(0)	–0.079(0)
Postmonsoon	**–0.162(1)****	–0.029(0)	**–0.167(0)****	0.002(0)	**–0.108(0)**
CAMS-3 (Darus Salam, Dhaka)					
Winter	**–0.457(0)****	**–0.193(1)****	–0.119(7)	**0.134(0)**	**–0.135(0)***
Premonsoon	**–0.500(0)****	0.177(14)	**–0.403(0)****	**0.127(0)**	**–0.110(0)**
Monsoon	**–0.560(0)****	0.082(–1)	–0.114(–2)	**0.156(0)**	**–0.137(0)**
Postmonsoon	**–0.432(0)****	0.040(0)	**–0.283(0)****	**0.141(0)**	**–0.136(0)**
CAMS-4 (Gazipur)					
Winter	**–0.480(0)****	**–0.191(2)***	**–0.202(1)****	**0.124(1)**	–0.023(0)
Premonsoon	**–0.376(0)****	**0.117(0)**	**–0.361(0)****	**0.113(0)***	**–0.108(0)**
Monsoon	**–0.518(0)****	**0.274(0)****	–0.173(–9)	**0.175(0)**	**–0.165(0)****
Postmonsoon	**–0.400(0)****	0.045(0)	**–0.253(0)****	**0.182(0)**	**–0.170(0)**
CAMS-7 (Agrabad, Chittagong)					
Winter	**–0.438(0)****	**–0.242(0)****	0.067(0)	**0.165(0)***	0.098(0)
Premonsoon	**–0.337(0)****	0.078(0)	**–0.336(1)****	0.073(0)	–0.083(0)
Monsoon	**–0.285(0)****	**0.144(0)****	**–0.306(0)****	**0.148(0)**	**–0.135(0)****
Postmonsoon	**–0.287(0)****	0.155(0)	**–0.405(0)****	**0.157(0)***	**–0.185(0)****
CAMS-8 (Sylhet)					
Winter	**–0.303(0)****	**–0.196(0)****	–0.080(0)	–0.076(0)	**–0.123(0)***
Premonsoon	**–0.361(0)****	**0.352(0)****	**–0.226(0)****	**0.155(1)***	**–0.230(0)****
Monsoon	**–0.357(0)****	**0.310(0)***	**–0.141(0)****	**0.182(0)****	**–0.226(0)****
Postmonsoon	**–0.282(0)****	**0.142(0)**	**–0.176(0)**	**0.156(0)**	**–0.229(0)****
CAMS-10 (Rajshahi)					
Winter	**–0.140(0)****	**–0.152(0)***	0.055(0)	**0.185(0)****	–0.022(0)
Premonsoon	–0.098(0)	0.021(0)	–0.093(0)	**0.221(0)****	0.047(0)
Monsoon	**–0.173(0)****	0.040(0)	**–0.136(0)***	**0.144(0)**	0.034(0)
Postmonsoon	**–0.220(0)****	–0.014(0)	**–0.136(0)**	**0.100(0)**	–0.026(0)
CAMS-11 (Barisal)					
Winter	**–0.297(0)****	**–0.232(2)****	**–0.146(1)****	**0.164(1)****	–0.056(0)
Premonsoon	**–0.367(0)****	0.023(0)	**–0.353(0)****	0.078(0)	–0.132(0)
Monsoon	**–0.378(0)****	**0.178(0)****	**–0.198(0)****	**0.111(0)****	–0.070(0)
Postmonsoon	**–0.402(0)****	–0.060(0)	**–0.328(1)****	**0.114(1)****	–0.129(0)

Statistical significance indicators are as follows: ** $p < 0.0001$; * $0.001 > p > 0.0001$. Here, WS = Wind Speed, WD = Wind Direction, T = Temperature, RH = Relative Humidity, SR = Solar Radiation, RD = Rainfall Duration.

brick kilns activities nearby the monitoring stations. The total number of legally registered brick kilns in Dhaka, Gazipur city, Chittagong, Sylhet, Rajshahi, and Barisal are 2295, 199, 1663, 257, 1176, and 366, respectively (FSFM, 2019). These brick kilns, located in the suburbs of major cities, operate fully during winter and primarily emit fine particles ($PM_{2.5}$). Therefore, in winter, when the temperature is lower, the emission of $PM_{2.5}$ to the atmosphere is more intense than that of PM_{10}, leading to a stronger negative correlation between $PM_{2.5}$ and temperature. Another noticeable fact is that, these correlations are obtained at a positive lag of 0–2 days, which indicates that it takes around 0–2 days to get a notable effect of temperature decrease on PM variation.

Table 3. Seasonal cross-correlation coefficients between meteorological parameters and PM_{10} over eight stations showing maximum correlation coefficients and corresponding lag period in days (in parenthesis).

	WS	T	RH	SR	RD
CAMS-1 (Sangsad Bhaban, Dhaka)					
Winter	**–0.326(0)****	**–0.236(1)****	**–0.157(1)****	**0.138(2)**	**–0.181(0)****
Premonsoon	**–0.310(0)****	0.074(0)	**–0.402(0)****	**0.111(2)**	0.033(1)
Monsoon	**–0.284(0)****	**0.161(0)****	**–0.162(0)****	**0.121(0)**	–0.029(0)
Postmonsoon	**–0.106(0)***	–0.103(–3)	**–0.203(0)****	0.082(0)	–0.006(0)
CAMS-2 (Farmgate, Dhaka)					
Winter	–0.088(0)	–0.010(0)	0.067(0)	0.006(0)	0.060(0)
Premonsoon	**–0.221(0)****	–0.075(0)	**–0.153(0)****	0.009(0)	**–0.120(0)***
Monsoon	**–0.185(0)****	0.018(0)	**–0.143(0)****	0.070(0)	–0.026(0)
Postmonsoon	**–0.180(0)***	0.031(0)	**–0.210(0)****	0.094(6)	**–0.133(0)**
CAMS-3 (Darus Salam, Dhaka)					
Winter	**–0.401(0)****	**–0.136(1)****	**–0.190(0)****	**0.151(0)****	**–0.163(0)****
Premonsoon	**–0.404(0)****	0.175(14)	**–0.485(0)****	**0.165(0)****	**–0.113(0)**
Monsoon	**–0.390(0)****	**0.231(0)****	**–0.251(0)****	**0.251(0)****	**–0.160(0)****
Postmonsoon	**–0.400(0)****	0.065(0)	**–0.377(0)****	**0.237(1)****	**–0.157(0)***
CAMS-4 (Gazipur)					
Winter	**–0.507(0)****	**–0.203(2)***	**–0.218(1)****	**0.174(1)****	–0.068(0)
Premonsoon	**–0.312(0)****	**0.281(0)***	**–0.416(0)****	**0.155(0)**	**–0.115(0)**
Monsoon	**–0.492(0)****	**0.383(0)****	**–0.220(0)****	**0.231(0)****	**–0.295(0)****
Postmonsoon	**–0.382(0)****	0.074(0)	**–0.319(0)****	**0.218(0)**	**–0.148(0)**
CAMS-7 (Agrabad, Chittagong)					
Winter	**–0.370(0)****	**–0.126(0)**	**–0.165(0)***	**0.220(0)****	0.097(0)
Premonsoon	**–0.286(0)****	**0.240(0)****	**–0.415(0)****	**0.148(0)****	**–0.183(0)****
Monsoon	**–0.215(0)****	**0.294(0)****	**–0.404(0)****	**0.306(0)****	**–0.256(0)****
Postmonsoon	**–0.246(0)****	**0.226(0)**	**–0.533(0)****	**0.295(0)****	**–0.187(0)****
CAMS-8 (Sylhet)					
Winter	**–0.268(0)****	–0.066(0)	–0.094(0)	–0.009(0)	**–0.201(0)****
Premonsoon	**–0.330(0)****	**0.395(0)****	**–0.422(0)****	**0.210(0)****	**–0.311(0)****
Monsoon	**–0.269(0)****	**0.425(0)****	**–0.313(0)****	**0.290(0)****	**–0.344(0)****
Postmonsoon	**–0.216(0)****	**0.195(0)****	**–0.306(0)****	**0.276(0)****	**–0.313(0)****
CAMS-10 (Rajshahi)					
Winter	**–0.123(0)****	**–0.158(0)***	–0.010(0)	**0.200(0)****	–0.058(0)
Premonsoon	**–0.120(0)****	0.045(0)	–0.085(–1)	**0.183(0)****	**–0.106(0)**
Monsoon	**–0.120(0)****	**0.224(0)****	**–0.303(0)****	**0.271(0)****	**–0.177(0)****
Postmonsoon	**–0.131(0)****	–0.004(0)	**–0.303(0)****	**0.252(0)**	**–0.139(0)***
CAMS-11 (Barisal)					
Winter	**–0.366(0)****	**–0.214(2)****	**–0.277(0)****	**0.202(1)****	–0.064(0)
Premonsoon	**–0.263(0)****	0.054(0)	**–0.515(0)****	**0.110(0)**	**–0**.125(0)
Monsoon	**–0.394(0)****	**0.421(0)****	**–0.331(0)****	**0.197(0)****	**–0.132(0)****
Postmonsoon	**–0.478(0)****	**0.233(0)****	**–0.491(0)****	**0.202(0)****	–0.131(0)

Statistical significance indicators are as follows: ** $p < 0.0001$; * $0.001 > p > 0.0001$. Here, WS = Wind Speed, WD = Wind Direction, T = Temperature, RH = Relative Humidity, SR = Solar Radiation, RD = Rainfall Duration.

During the monsoon season, the highest positive correlation between temperature and PM is observed with no lag or no lead, indicating an immediate response of PM to the change of temperature. High-temperature conditions and a warm rainy season usually favor the formation of bioaerosols (Ahmed *et al.*, 2013), and probably due to this reason, a positive correlation between temperature and PM during these seasons is observed. Since daytime temperature is more conducive to biogenic volatile organic compound (BVOC) formulation amidst forest environment (Liu *et al.*, 2015; Perlwitz and Miller, 2010; Holmes, 2007), this might be responsible for a stronger (relative to other stations) positive correlation between temperature and PM in Sylhet.

Postmonsoon shows a weak positive correlation between temperature and PM for most stations, except Chittagong and Barisal, where a moderately strong positive correlation is observed (especially for PM_{10}). Such a strong correlation might attribute to the coastal proximity of these stations. Sea-surface cools more slowly than land-surface, requiring more time to lower the ambient temperature (Jayamurugan *et al.*, 2013). As a result, the climate of postmonsoon remains almost the same as that of monsoon in these two locations. Owing to this reason, the correlation coefficient of postmonsoon temperature and PM is possibly similar to that of monsoon season.

3.3.3 Relative humidity and rainfall duration

A strong negative correlation between relative humidity and PM occurs during premonsoon and postmonsoon. Although high humidity persists in monsoon, this season exerts a weaker correlation than premonsoon. In addition, the frequency and durability of precipitation events increase rapidly during the monsoon season, making the influence of relative humidity insignificant on PM. Besides, PM starts to reduce during premonsoon, and at the end of the season, the ambient PM level becomes moderate or insignificant. Therefore, the effect of relative humidity on PM removal in monsoon cannot become as prominent as in premonsoon since most of the PM removal has already been taken place in the premonsoon season.

On the contrary, the highest negative correlation between rainfall duration and PM occurs during monsoon (Table 2 and Table 3). Since monsoon season is characterized by heavy and persistent rainfall, it results in higher PM removal in this season by wet deposition, leading to a negative association between the pair.

3.3.4 Solar radiation

All stations show a positive correlation between solar radiation and PM throughout the year, as shown in Table 2 and Table 3. Here, it can be observed that the highest positive correlation mainly occurs during the monsoon season. Monsoon is characterized by high incident solar radiation, which favors frequent new particle formation (NPF) events. Additionally, condensation sink remains low in monsoon as PM concentration (pre-existing aerosol) becomes lower, leading to a favorable environment for NPF (Wonaschütz *et al.*, 2015; Vehkamaki *et al.*, 2004). This phenomenon may result in a stronger positive correlation between PM and solar radiation during monsoon. The second highest correlation is observed in the postmonsoon season. The environment conducive to NPF in monsoon still prevails in the postmonsoon. Additionally, after monsoon rainfall, vegetation and grass cover growth also favors particle formation events (Salma *et al.*, 2021; Ganguly *et al.*, 2006).

3.4 Multiple Non-linear Regression Analysis (MNLR)

The results of MNLR analysis for daily PM and meteorological variables are shown in Table 4. Besides, the details of selected seasonal MNLR models for $PM_{2.5}$ and PM_{10} with adjusted r^2 values, PRESS values, F-statistics, *p*-values and Durbin Watson values are presented in Table S6 and Table S7. Here, the model with the lowest PRESS and highest adjusted r^2 value is selected for each case. For ease of explanation, wind speed, temperature, relative humidity, solar radiation, and rainfall duration are denoted as WS, T, RH, SR, and RD, respectively. Table S6 and Table S7 show that inclusion of lag and interaction terms notably increase the efficacy of the model. For example, prediction efficacy increases from 23% to 36%, when lead term of temperature and interaction terms are included into the model for winter $PM_{2.5}$ prediction in Darus Salam station of Dhaka (CAMS-3). Similar results are observed for other cases. This finding is aligned with an earlier study that meteorological information of previous days can be used as important factors for the prediction of PM variation (Chen *et al.*, 2018).

Table 4 shows that the adjusted r^2 is higher during post-monsoon (70%–31%) and pre-monsoon (64%–29%), whereas it is moderate during winter (39%–11%) and monsoon (49%–13%). This indicates that PM variability is substantially influenced by meteorology throughout the year. However, the rest of the PM variation is modulated by other unknown factors that are not considered in our model. Examining the generated models for all cases (total 64 models), it is observed that the interaction term of wind speed and relative humidity (WS × RH) prevails throughout the year. On the other hand, T × RH is present in winter and postmonsoon, and SR × RH

Table 4. Results of MNLR analysis for daily PM and meteorological variables.

	$PM_{2.5}$		PM_{10}		Major interaction terms
	Adjusted r^2	PRESS	Adjusted r^2	PRESS	
CAMS-1 (Sangsad Bhaban, Dhaka)					
Winter	**0.199****	**2466**	**0.290****	**4938**	T × RH, SR^2, RH × SR
Premonsoon	**0.424****	**1304**	**0.469****	**1467**	WS × RH, RH^2
Monsoon	0.056	842	**0.208****	**989**	WS × RH, T × SR
Postmonsoon	**0.212****	**1125**	**0.378****	**2923**	RH^2, WS × RH, SR^2
CAMS-2 (Farmgate, Dhaka)					
Winter	0.086	1379	**0.193****	**5001**	WS × SR, RH × SR
Premonsoon	**0.358****	**1199**	**0.269****	**2032**	WS × T, WS × SR
Monsoon	**0.125****	**393**	**0.182****	**933**	RH × SR, WS × RH
Postmonsoon	**0.219****	**1185**	**0.248****	**3021**	WS × RH, RH × RD
CAMS-3 (Darus Salam, Dhaka)					
Winter	**0.351****	**2408**	**0.245****	**5764**	WS × T, WS × RH, T × RH
Premonsoon	**0.643****	**1207**	**0.647****	**2616**	RH^2, WS × T
Monsoon	**0.252****	**267**	**0.348****	**573**	WS × RH
Postmonsoon	**0.601****	**1462**	**0.677****	**1562**	T × RH, T × SR
CAMS-4 (Gazipur)					
Winter	**0.281****	**1831**	**0.442****	**3179**	T × RH, WS × T, WS × RH
Premonsoon	**0.560****	**1062**	**0.792****	**3056**	WS × RH, RH, T
Monsoon	**0.398****	**136**	**0.452****	**513**	WS × SR, RH × SR, WS × RH
Postmonsoon	**0.636****	**991**	**0.801****	**2875**	WS×RH, T×RH, SR×RD
CAMS-7 (Agrabad, Chittagong)					
Winter	**0.389****	**1069**	**0.333****	**2055**	T × RH, WS × RH
Premonsoon	**0.453****	**547**	**0.487****	**1570**	T × RH, WS × RH, T^2
Monsoon	**0.329****	**122**	**0.326****	**606**	WS × RH, RH^2, SR × RD
Postmonsoon	**0.645****	**507**	**0.742****	**1288**	T × RH, WS × RH, WS × SR
CAMS-8 (Sylhet)					
Winter	**0.210****	**1203**	**0.226****	**2334**	WS × RD, T^2
Premonsoon	**0.512****	**557**	**0.602****	**1597**	RH^2, WS × SR, T × SR
Monsoon	**0.161****	**93**	**0.312****	**267**	WS × RH, SR × RD, T^2
Postmonsoon	**0.313****	**445**	**0.504****	**962**	T × RH, SR × RD
CAMS-10 (Rajshahi)					
Winter	**0.113****	**1759**	0.083	4503	WS × T
Premonsoon	**0.297****	**586**	**0.162****	**4015**	T × RH, RH × SR
Monsoon	0.046	322	0.086	2086	RH × SR
Postmonsoon	**0.327****	**1591**	**0.336****	**2846**	T × RH, WS^2
CAMS-11 (Barisal)					
Winter	**0.156****	**2787**	**0.402****	**2748**	T × RH, WS × RH, $T(2)^2$
Premonsoon	**0.529****	**386**	**0.656****	**699**	T × RH, WS × SR, T × SR
Monsoon	**0.466****	**128**	**0.451****	**280**	WS × RH, T× SR, WS × SR
Postmonsoon	**0.694****	**708**	**0.739****	**1285**	T × RH, WS × SR, T × SR

Statistical significance indicators are as follows: ** $p < 0.0001$; * $0.001 > p > 0.0001$, otherwise $0.01 > p > 0.001$. Here, WS = Wind Speed, WD = Wind Direction, T = Temperature, RH = Relative Humidity, SR = Solar Radiation, RD = Rainfall Duration.

and SR × RD are prominent in premonsoon and monsoon. Therefore, solar radiation individually may not affect PM variation strongly, but it exerts a powerful influence in association with other parameters. The presence of interaction terms SR × RH and SR × RD during monsoon indirectly supports our hypothesis on NPF events that solar radiation accelerates particle formation in the presence of moisture during monsoon.

The most substantial meteorological influence is observed in Chittagong, followed by Barisal from the station-wise analysis. Strong meteorological influence on PM variation suggests that regulatory measures should focus on climatological influence, transboundary pollution and anthropogenic emission to sufficiently reduce PM pollution in these areas. On the other hand, lower meteorological influence is observed in Rajshahi and Dhaka (Sangsad Bhaban and Farmgate). This suggests that regulatory measures should primarily focus on anthropogenic emission reduction in these locations.

Using dominance analysis (Afrin *et al.*, 2021; Tonidandel and LeBreton, 2011; Azen and Budescu, 2003), we determined the relative contribution of each meteorological parameter to the total variation of PM in each season to demonstrate how the relative contribution of meteorological parameters vary over seasons for the PM fractions. We performed this analysis for the MNLR models without the interaction terms, considering Chittagong station (CAMS-7) as a sample location. The result of this analysis is presented in Fig. 3. In general, temperature, relative humidity and wind seemed to have major contribution to total variation of both $PM_{2.5}$ and PM_{10}. Temperature showed higher contribution to $PM_{2.5}$ variation than PM_{10} in all seasons, while the opposite is observed for relative humidity. A similar finding is observed in a previous study- based on Dhaka city, Bangladesh (Afrin *et al.*, 2021). Fig. 3 also shows the change in contribution from meteorological parameter over seasons. For both PM fractions, temperature had the highest contribution in winter, whereas for relative humidity, it was in the postmonsoon season. During the other two seasons (i.e., premonsoon and monsoon), wind speed and direction dominated the overall PM variation. Solar radiation and rainfall duration seemed to be minimal contribution, although the contribution rose for PM_{10} during the monsoon season.

Although presenting PM prediction models was not an objective of this study, we performed model validation of our MNLR models considering Chittagong station (CAMS-7) as a sample location for a recent dataset from 2019 to 2021. Fig. 4 and Fig. 5 represent the results of the validation process. The time series plots of observed and modeled $PM_{2.5}$ and PM_{10} concentrations are shown in Figs. 4(a) and 4(b). These figures imply that the model prediction was better for PM_{10} compared to $PM_{2.5}$. The season wise scatter plots (Fig. 5) of modeled versus observed PM concentrations indicate that model predictions vary over seasons, as observed in a previous study (Afrin *et al.*, 2021). Overall, the time series plots of the actual and predicted PM (Fig. 4) and the moderate correlation coefficients (r = 0.33–0.76) between them (Fig. 5) indicate that these MNLR models can capture the seasonal variability of PM to some extent.

4 CONCLUSION

This study analyzed temporal and spatial variation of meteorological influence on PM concentration

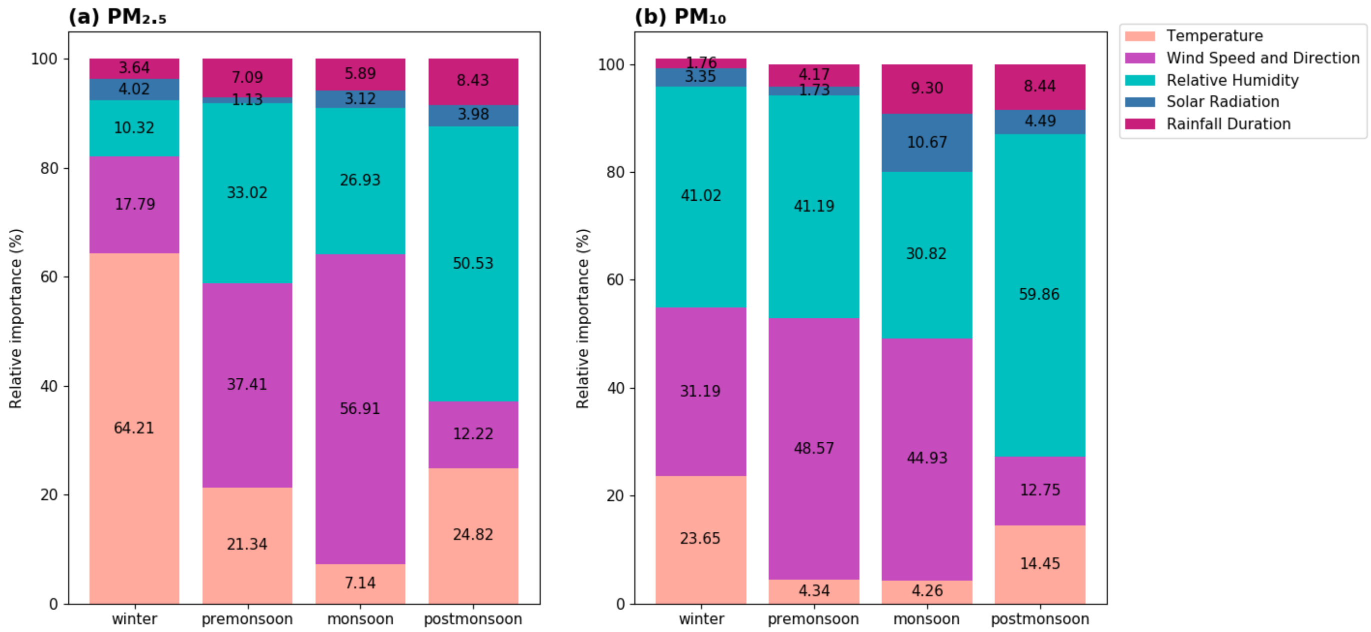

Fig. 3. The relative contribution of each meteorological factors in explaining the total $PM_{2.5}$ and PM_{10} variability in CAMS-7 of Chittagong.

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https://doi.org/10.4209/aaqr.220082

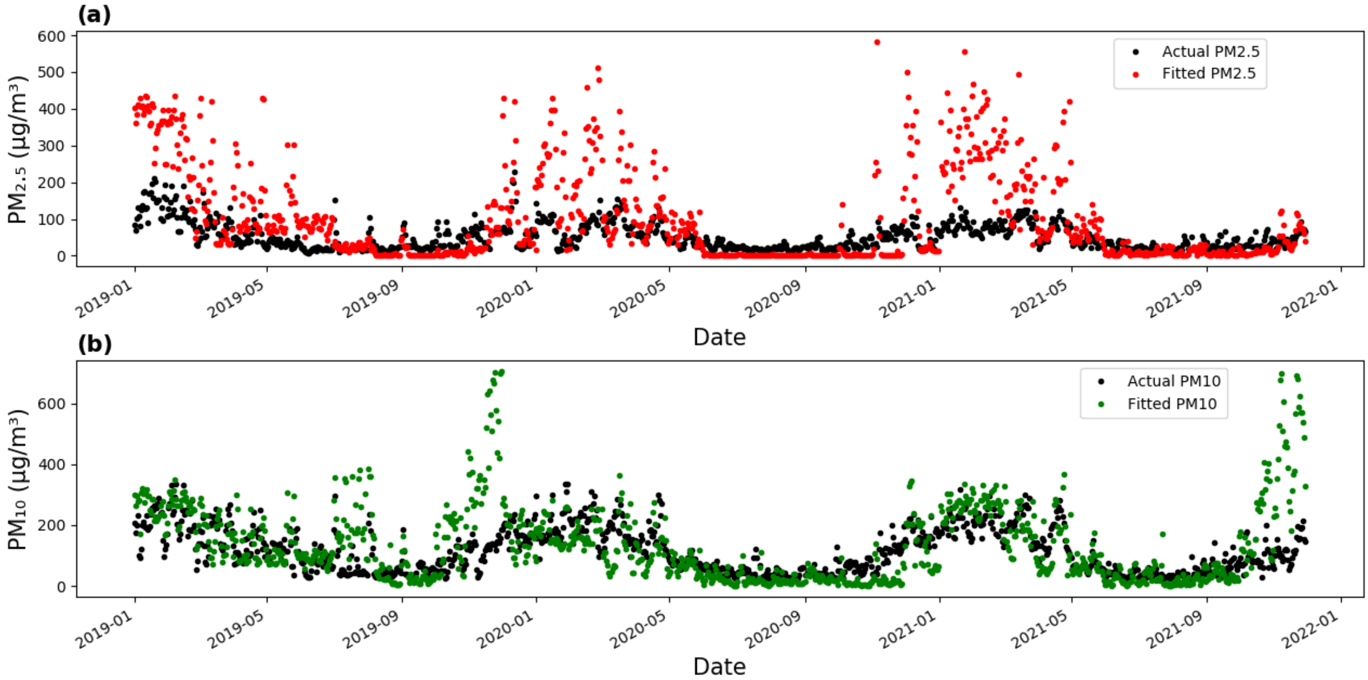

Fig. 4. Time series plot of actual and fitted (a) $PM_{2.5}$ and (b) PM_{10} concentration in CAMS-7 of Chittagong.

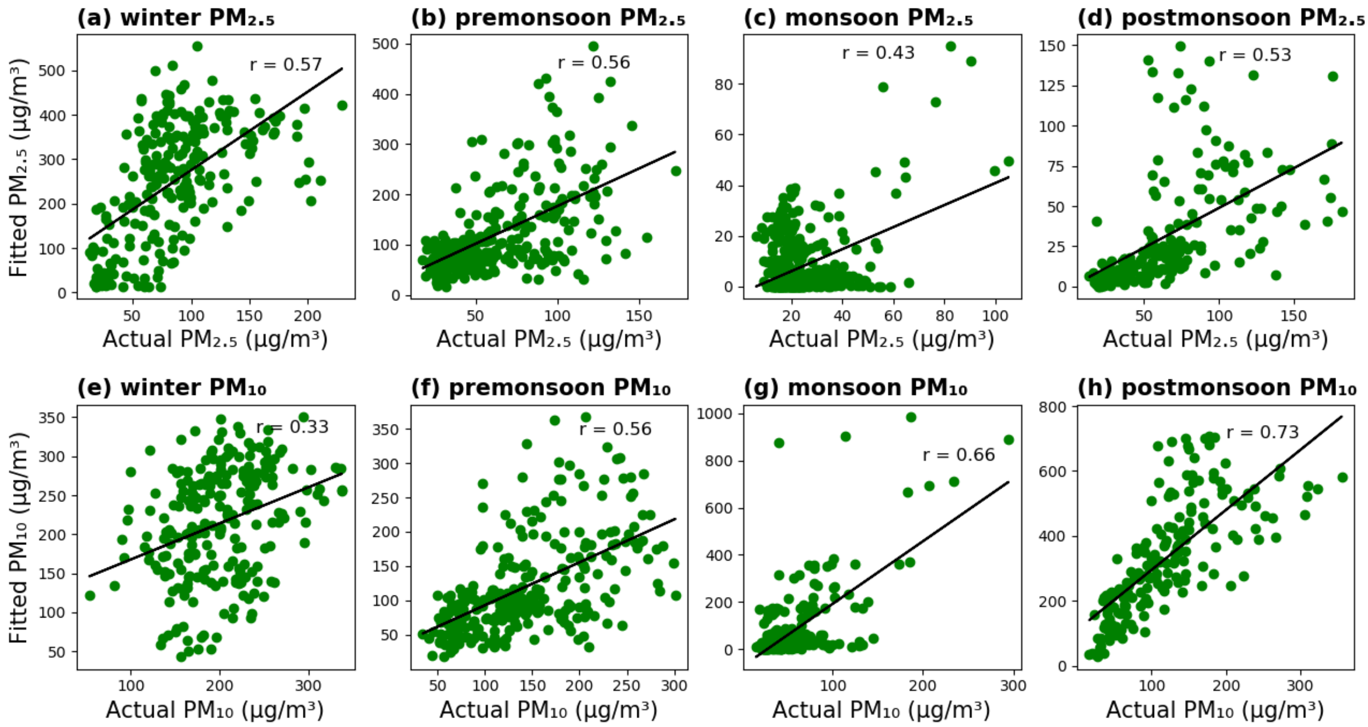

Fig. 5. Scatter plot of Fitted vs. actual (a–d) $PM_{2.5}$ and (e–h) PM_{10} concentration for four seasons in CAMS-7 of Chittagong.

over major urban areas of Bangladesh from 2013 to 2018. Annual and seasonal cross-correlation analyses were performed to identify major influential parameters on PM variation at different times of the year. In addition, seasonal multiple non-linear regression analysis (MNLR) using interaction and lagged terms was performed to understand the internal association of meteorological parameters with each other and their combined effect on particulate matter.

Annual cross-correlation analysis shows that wind speed, humidity, and rainfall are negatively correlated and solar radiation is positively correlated with PM concentration. Temperature shows a negative correlation with PM for most stations. However, the pair is positively correlated for stations located in the eastern part of the country. Wind flow coming from the northwestern direction is presumed to carry higher PM loading. Brick kilns and transboundary pollution are identified as potential aerosol sources coming from this direction.

Seasonal cross-correlation analysis shows that wind speed, humidity, and rainfall are negatively correlated, while solar radiation is positively correlated with PM throughout the year. However, for temperature and PM pair, a negative correlation is observed during winter and a positive correlation is observed during other seasons. The coastal proximity generation of monsoon sea-aerosol in Chittagong, premonsoon Norwester in Barisal, high plantation cover in Sylhet are presumed to influence PM concentration. Relative humidity and PM strongly correlate inversely during premonsoon and postmonsoon whereas, rainfall is prominent on PM during monsoon. The effect of rainfall is most substantial in Sylhet, the zone of maximum rainfall in the country. Finally, solar radiation and PM show maximum positive correlation during monsoon, indicating a combined influence of solar radiation and atmospheric moisture on new particle formation. MNLR analysis indicates that meteorological influence is the strongest in Chittagong and Barisal and the weakest in Dhaka and Rajshahi. The study indicates that while meteorological factors can influence the seasonal variability of PM, the extent of the influence can be modulated by local and regional factors. Therefore, a single meteorology-based PM prediction model may not be useful for different spatial scales, where topographic and other differences exist. This study is the first of its kind to identify spatial heterogeneity of meteorological influences on seasonal PM variation in different cities of Bangladesh.

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SUPPLEMENTARY MATERIAL

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