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ORIGINAL PAPER

Spatio-temporal variations in the estimation of PM_{10} from MODIS-derived aerosol optical depth for the urban areas in the Central Indo-Gangetic Plain

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Abstract Particulate air pollution poses a serious health problem to the urban centers in the central Indo-Gangetic plain (IGP) in northern India. Health management planning is constrained by the lack of availability of continuous dataset of particulate matter (PM) at a regional scale. Recently, researchers have established the strength of regression models for estimating PM from satellite-derived aerosol optical depth (AOD) and meteorological factors. The present study is focused on three cities, namely, Agra, Kanpur and Varanasi located in the central IGP. The study envisages four approaches of multi-linear regression modeling to estimate PM_{10} (particulates smaller than 10 μm) from AOD and the meteorological parameters. The first approach consists of four regional models, three of which estimate regional mean PM_{10} and the fourth one estimates the distributed PM_{10}. These models have a weak-to-moderate coefficient of determination ($R^2 = 0.37$–0.63). Spatial and temporal variations in the estimators are separately addressed by the second modeling approach, i.e., city models (CMs) and the third modeling approach, i.e., seasonal models (SMs), respectively. R^2 of these models varies from 0.40 to 0.68. Finally, the spatio-temporal variability of the estimators are addressed by the fourth modeling approach, i.e., city-wise seasonal models (CSMs) which exhibited better results ($R^2 = 0.49$–0.88). Remarkable variations in the regression estimators of the CSMs are observed both spatially and temporally. The model adequacy checks and the validation studies also support CSMs for more reliable estimation of PM_{10} in the central IGP. The proposed methodology can, therefore, be reliably used in generating the regional PM_{10} concentration maps for health impact studies.

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1 Introduction

It is estimated that approximately 3 % of cardiopulmonary and 5 % of lung cancer deaths can be attributed to the particulate matter (PM) globally (WHO 2013). Citing the recently released global burden of disease (GBD) report, Centre for Science and Environment, India (CSE), has stated that the air pollution was the fifth leading cause of death in India, with 620,000 premature deaths in 2010. This was a sixfold increase from 100,000 in the year 2000 (CSE 2013). Respiratory and cardiovascular diseases are the key reasons for air pollution-induced premature deaths. These diseases include stroke (25.48 %), chronic obstructive pulmonary disease (17.32 %), ischemic heart disease (48.6 %), lower respiratory infections (6.4 %), and trachea, bronchus and lung cancer (2.02 %). In the wake of the GBD findings, CSE has also analyzed the latest air quality data available from the Central Pollution Control Board (CPCB) for the year 2010 and found that half of the urban population breathed air laced with particulate pollution that exceeded the Indian standards. In India, the PM_{10} standards have been prescribed both for annual mean and for daily mean values as 60 and 100 μg/m^3, respectively. Further, about one-third of the population was exposed to critical levels of particulate pollution, i.e., exceeding the standard by over 1.5 times. Smaller and more obscure cities were amongst the most polluted. In India about 78 % cities (141) exceed the PM_{10} standard; 90 cities had critical levels of PM_{10}; and 26 cities had the most critical levels, i.e., exceeding the standard by over three times (CSE 2013).

The conventional techniques of PM measurement have limited capability to define the regional air quality with reasonable spatial resolution and thus the efficacy of studies related to the regional health management is constrained. Satellite remote sensing provides the required spatial coverage in examining the air quality at the regional (Dey et al. 2012) or global scale (Hoff and Christopher 2009; van Donkelaar et al. 2010). Satellite sensors indirectly retrieve the columnar aerosol presence in terms of aerosol optical depth (AOD) by measuring the electromagnetic radiation scattered back to the top of the atmosphere from the earth's surface and from the atmosphere itself. The moderate resolution imaging spectroradiometer (MODIS) sensor onboard the Terra (morning) and Aqua (afternoon) satellites acquire the information in 36 different wavelength channels. Seven of these wavelength channels (between 0.47 and 2.12 μm) are used for the aerosol retrieval. In the collection five retrieval algorithm, three different channels of 0.47, 0.66 and 2.12 μm are primarily employed for overland aerosol retrievals, while many other channels are used for screening procedures (e.g., cloud, snow and ice cover, etc.). These three channels are simultaneously inverted to finally report AOD_{MODIS} values at the wavelength of 0.55 μm (Levy et al. 2010; Lee et al. 2011).

The satellite-retrieved AOD has been used as the main input parameter in many models to predict the ambient $PM_{10}/PM_{2.5}$ concentration (Wang and Christopher 2003; Chu et al. 2003, 2006; Othman et al. 2009; Lee et al. 2011; Yap and Hashim 2013). The AOD–PM association is also influenced by the meteorological and seasonal parameters. The meteorological factors have, therefore, been assimilated to depict the ambient impacts on PM, and thus the simple linear regressive models are replaced with nonlinear and multi-linear models to improve the correlation between AOD and PM concentrations (Li et al. 2005; Gupta et al. 2006; Gupta and Christopher 2008, 2009a; Kumar et al. 2007, 2008, 2013; Hoff and Christopher 2009; Liu et al. 2009; van Donkelaar et al. 2010). Apart from the meteorological factors, temporal factors have also been incorporated in the regression models to further improve the model capabilities to predict the PM concentration reliably and robustly (Li et al. 2005; Gupta et al. 2006; Gupta and Christopher 2008; Lee et al. 2011).

As per the findings of various studies conducted for the urban centers of Central Indo-Gangetic Plain (IGP) in northern India, the lowest PM concentration has been observed during the monsoon season and the highest concentration in the winter season (Tare et al. 2006; Chakraborty and Gupta 2010; Singh and Sharma 2012; Pachauri et al. 2013). The maximum aerosol loading in the atmospheric column was reported during the months of April–May, i.e., pre-monsoon season (Singh et al. 2004; Poarch et al. 2007; Choudhry et al. 2012 and Ramachandran et al. 2012).

In the present study, our intent is to utilize the MODIS AOD retrievals and coincidental meteorological parameters to develop regression models with different approaches to examine the spatial and temporal variability of estimated PM_{10} in the urban areas of the central part of the IGP. Such models are useful in filling in the gaps in PM_{10} at regional level, which is required to examine the air quality of the region. These models can also help in the development of the regional air quality index (AQI) related to the particulate pollution and consequently in the policy formulation related to the health management strategies of the region.

2 Study area

In general, studies involving the regression analysis for establishing the PM–AOD association for a given region must incorporate PM and other ground measurements data from multiple sites with different background over the entire region. However, in India, there is a very limited availability of the desired data for the rural regions or country areas which are generally clean; as the government agencies have been focusing only on the urban centers for continuous air quality monitoring. Therefore, in the present study, the urban centers in the central part of IGP were the focus for PM–AOD modeling. For this reason, the study area or the study region has been defined as a set of urban centers located in the central IGP. There are more than 60 urban centers (cities and towns) in the central IGP which covers most of the area of the state of Uttar Pradesh (UP), India. Almost all of these urban centers are infested with high PM pollution and have similar meteorology and anthropogenic activities. Three cities of UP, namely, Agra, Kanpur and Varanasi have been chosen as the sites for the ground data monitoring for the present study. The locations of these three cities are evenly distributed across the central IGP (Fig. 1). The average meteorological and PM pollution features across these three cities may, therefore, fairly represent the regional features. The reason for focusing these three cities of UP was also the fact that these cities were the first to be provided an automatic air quality monitoring station (AAQMS) by Uttar Pradesh Pollution

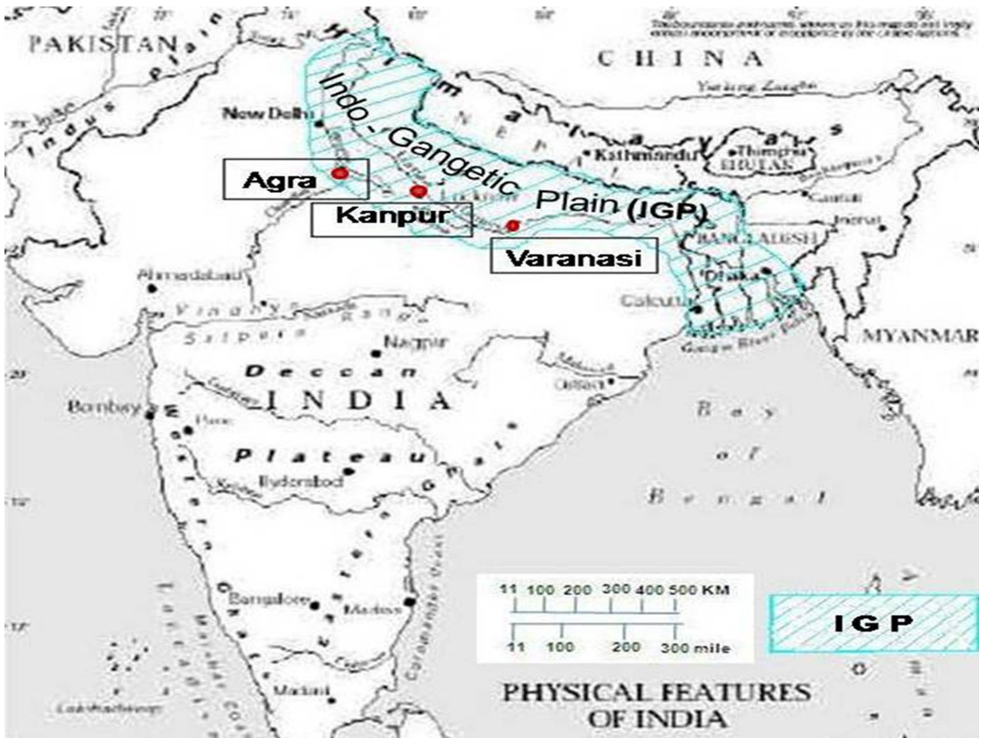

Fig. 1 Central Indo-Gangetic plain—the study area

Control Board (UPPCB) to continuously monitor the air quality including the PM and the meteorological parameters since the year 2010. A brief description on the background of each monitoring site is presented below.

Agra City enjoys the reputation of being an internationally famous tourist destination because of the "Taj Mahal" and other historical monuments. The city has many small-scale and cottage industries in its periphery. The AAQMS is installed here on the Nagar Nigam building near Sanjay Palace with geographical location as 27°12′12.26″N, 78°00′21.03″E, 122.26 m elevation (above mean sea level). The area surrounding the monitoring station is relatively cleaner and has a light traffic volume mainly due to office activities. The monitoring site is located about 200 m away from the busiest road of the city and has a heavy volume of mixed traffic. Kanpur City is the largest industrial city of Uttar Pradesh with a dense population. The AAQMS is located near the Brahma Nagar crossing with geographical location as 26°28′27.00″N, 80°19′56.26″E, 128.96 m elevation (above mean sea level). The main source for air pollution in the vicinity of AAQMS is office traffic and other routine anthropogenic activities. Varanasi City is an ancient center of Indian culture and religion. It is a revered city for all Hindus and Buddhists worldwide. The city has relatively high population density. Here the AAQMS is located on Varanasi–Lucknow National Highway-56 near orderly market (25°20′59.23″N, 82°58′44.67″E, 82.93 m elevation above mean sea level). The site receives the air pollution from the vehicular activities and from nearby cottage industrial sources. Here also the traffic volume is reasonably high with mostly local transport vehicles.

3 Data availability

The data for this study were obtained from two sources. The Collection 5 (C005) AOD data from the MODIS sensors onboard Terra and Aqua Satellites were retrieved from the Level 1 atmosphere archive and distribution system (LAADS) website of National Aeronautics and Space Administration (NASA) for all the three cities and for the study period of 3 years, i.e., from January 2010 to December 2012. The Level 2 AOD data (at 10×10 km resolution) were extracted for the pixels overlying the ground measurements sites in the three cities. The hourly data sets of PM_{10} and the meteorological parameters, namely, relative humidity (RH), wind speed (WS) and atmospheric temperature (AT) coincident to AOD_{MODIS} retrievals were obtained from the established AAQMS. These AAQMS housed the Met One BAM-1020 instrument that automatically measured and recorded the data of the ambient air quality including PM and meteorological parameters every hour for the entire day. In the present study, a single data set is defined as the coincident observations of the five parameters, namely, PM_{10}, AOD_{MODIS}, RH, WS and AT monitored at the time of MODIS sensor overpassing the AAQMS sites. This overpass happened twice a day (10:30 a.m. for the Terra and 1:30 p.m. for the Aqua satellite). The regression models have used both of these overpass observations as independent data sets. Thus, the hourly data sets desired for the present study were procured twice a day for the entire study period.

The bias or error in AOD retrievals could arise from various sources including incorrect assumptions about surface reflectance, aerosol type, status of sensor calibration and observation geometry, etc. (Levy et al. 2010). The quality of the C005 AOD retrieval overland was evaluated globally by Levy et al. (2010) to characterize systematic error sources with respect to Aerosol Robotic Network (AERONET) observations. They found more than 66 % of AOD_{MODIS} comparable to AERONET-retrieved AOD within an expected error envelop, $\Delta AOD = \pm(0.05 + 0.15AOD)$ with a high correlation ($R = 0.9$). Terra's global AOD bias was found changed with time, overestimating by ~ 0.005 before 2004 and underestimating by a similar magnitude after due to calibration uncertainty. Jethva et al. (2007) have found nearly 70 % of the retrievals falling within the expected error envelope, $\Delta AOD = \pm\ (0.05 + 0.15\ AOD)$ with a high correlation ($R = 0.91$) based on the comparison with $AOD_{AERONET}$ retrieved from Kanpur AERONET station. The absolute error/bias in retrieval of AOD_{MODIS} increases with AOD_{MODIS} over the central IGP region linearly with a correlation coefficient of 0.49 (Tripathi et al. 2005). The quality of the retrieval is better during the post-monsoon (October–November) to winter (December–February) season, while the dominance of dust results in larger error in the retrieved AOD during the pre-monsoon (March–May) and monsoon (June–September) seasons.

BAM-1020 measures the airborne particulate concentration using the principle of beta ray attenuation. A measured amount of dust-laden air is pulled through a filter tape and then dust-loaded filter is automatically placed between the source of high-energy electrons known as beta particles and the detector thereby causing an attenuation of the beta particle signal. The degree of this attenuation is used to determine the mass concentration of particulate matter (Met One Inc. 2008). The BAM data are also associated with some measurement errors. The BAM-1020 instrument performs continuous user-selected evaluation with a variety of criteria for data validation including flow statistics and a comprehensive set of error codes including power failures, flow failures, hardware failures, tape errors, nozzle errors, span check errors, beta count errors, and more. According to BAM manual, the accuracy of instrument exceeds US-EPA Class III $PM_{2.5}$ FEM standards for additive and multiplicative bias. The measurement accuracy of the instrument is reported as ±8 % of indication for 1 h mode and ±2 % compared to FRM for 24-h mode.

The data sets of the years 2010 and 2011 were used for the development of regression models and those of the year 2012 were used for the validation studies in all the cases. The temporal variation in the regression estimators are studied separately for the four seasons—winter, pre-monsoon, monsoon and post-monsoon.

4 Modeling approaches

The present study intended to develop suitable multi-linear regression models for reliably estimating PM_{10} concentrations in the urban centers of central IGP using AOD_{MODIS} and meteorological parameters as regressors. A simple multi-linear regression model using AOD_{MODIS}, RH, WS and AT as regressors is able to estimate appropriately the hourly PM_{10} levels in Agra City (Chitranshi et al. 2014). As the present study of regression modeling has been focused on the three distant cities of the central IGP, it is quite appropriate to consider various approaches of the model development keeping in mind the possibility of spatio-temporal variations in the regression estimators. The spatial variation of estimators could be attributed to the local sources (e.g., traffic pattern, land use and other anthropogenic activities) which may vary from city to city and are responsible for the generation of particulate pollution. Climatic conditions and anthropogenic activities of the region which may change from season to season could be responsible for the temporal variations in the estimators. Considering the various options of estimators' variations, following modeling approaches are proposed.

4.1 Regional models

In this approach, the estimators of the multi-linear regression model were assumed to have no substantial variation either spatially or temporally. In other words, the estimators were to remain practically constant over the entire region throughout the year. This assumption led to the concept of regional models. A regional model could be developed in following two ways.

4.1.1 Mean regional model (MRM)

Firstly, a regional model was developed based on the regional means, i.e., three cities' averages of the coincidental observations of PM_{10} and of regressors to estimate a regional mean PM_{10} value corresponding to an MODIS overpass. Such a model is termed as MRM and is expressed as:

$$\overline{PM_i} = \alpha + \beta_1\overline{AOD_i} + \beta_2\overline{RH_i} + \beta_3\overline{WS_i} + \beta_4\overline{AT_i} + e_i, \tag{1a}$$

where suffix i refers the serial number of the data set; bar above each parameter indicates its regional mean value; e_i is the residual error (i.e., observed $\overline{PM_i}$ − estimated $\overline{PM_i}$); α and βs are the regression estimators of the region as a whole; and all other terms have their usual meanings.

The concept of the above mean regional modeling has also been applied for the separate data sets corresponding to Terra overpass and Aqua overpass leading to the development of two additional mean regional models, namely, MRM_T for the Terra data and MRM_A for the Aqua data.

4.1.2 Regional distributed model (RDM)

As a second alternative, a regional model was developed by pooling all the data sets of all the cities together for the whole study period giving rise to a good number of data sets. This model can estimate the PM_{10} at any AOD pixel in the entire region provided the values of the regressors at the ground point overlaid by that pixel are known. Therefore, such a regional model is termed as RDM and is expressed as,

$$PM_i = \alpha + \beta_1 AOD_i + \beta_2 RH_i + \beta_3 WS_i + \beta_4 AT_i + e_i \tag{1b}$$

where the regressor parameters values are defined at preassigned pixels and all other terms have their usual meanings as defined earlier.

4.2 City models (CMs)

In this modeling approach, it is presumed that the regression estimators have significant spatial variations without any significant temporal variations. These variations are attributed to spatially varied conditions mentioned in the beginning of the approach. For this purpose, the entire data of the study period are to be pooled city-wise. Accordingly, the model is termed as CM and is expressed as:

$$PM_i^r = \alpha^r + \beta_1^r AOD_i^r + \beta_2^r RH_i^r + \beta_3^r WS_i^r + \beta_4^r AT_i^r + e_i^r, \tag{2}$$

where suffix 'i' refers the serial number of the data point; the superscript 'r' represents the city and all other terms have their usual meanings.

The regression estimators for a city remain constant throughout the year or through all the seasons but may vary from city to city area. Thus, three CMs are to be developed for the three selected cities and each CM can estimate the MODIS overpass PM_{10} for the city provided the corresponding values of the regressors are known.

4.3 Seasonal models (SMs)

Contrary to the city models, the regression estimators in this case are supposed to have substantial temporal variations without any significant spatial variations. For this category of modeling, the data are to be pooled season-wise over the entire region for the whole study period and thus, leading to the nomenclature of this type of model as SM which is expressed as,

$$PM_i^s = \alpha^s + \beta_1^s AOD_i^s + \beta_2^s RH_i^s + \beta_3^s WS_i^s + \beta_4^s AT_i^s + e_i^s \tag{3}$$

where suffix 'i' refers the serial number of the data point; superscript 's' represents the season and all other terms have their usual meanings as in the previous models.

The SMs are, therefore, supposed to provide the PM_{10} estimates season-wise only for a particular overpass pixel overlaid on the ground.

4.4 City-wise seasonal models (CSMs)

As a last and fourth option, the regression estimators are presumed to have both spatial and temporal variations implying that the estimators not only vary from city to city (spatially), but also from season to season (temporally). In this case, the development of four distinguished seasonal regression models for each of the three cities was envisaged. The data sets pooled for each of the city were segregated by season and the models were developed accordingly as CSMs which are expressed as:

$$PM_i^{r,s} = \alpha^{r,s} + \beta_1^{r,s} AOD_i^{r,s} + \beta_2^{r,s} RH_i^{r,s} + \beta_3^{r,s} WS_i^{r,s} + \beta_4^{r,s} AT_i^{r,s} + e_i^{r,s}, \tag{4}$$

where suffix 'i' refers the serial number of the data point; the superscript 'r' represents the city; the superscript 's' represents the season in the rth city and all other terms have their usual meanings.

4.5 Adequacy check and validation studies

Straight line scatter plots of the observed responses against the modeled responses are generally employed to assess the suitability of the model application. However, after analyzing the usage of scatter plots in detail, Chitranshi et al. (2014) have found that the information and inferences provided by such plots can also be derived theoretically by the regression results itself. The intercept and slope of such a plot are the functions of coefficient of determination (R^2)

and the mean of the observed responses ($\overline{PM_i}$). In addition, the correlation between modeled and observed responses has also been found the same as that of the developed regression model. Thus, the present study has not employed the redundant exercise of aforesaid scatter plotting. A better approach for checking the adequacy of the model was advocated by Johnson (2005). This approach is based on the basic assumption involved in the linear regression modeling that the residual errors, e_i are independent of estimated responses and should have the same variation as σ^2 of the observed responses. Therefore, the adequacy of the model can easily be checked by plotting the residuals against the estimated values. A plot having all the points confined to a horizontal band around the zero e_i line suggests the model to be an adequate one. Other defined trend of residuals may suggest the need of the transformation of the proposed model and/or addition of the square terms of the independent variables. Any undefined trend of the residuals may suggest the model as inadequate (Johnson 2005).

The model validation study was done by comparing the observed PM_{10} data of the validation period, i.e., year 2012 with the PM_{10} estimated by the already developed regression model using the observed AOD_{MODIS} and the meteorological parameters of the year 2012. The validation R^2 values were to be calculated accordingly and then compared with the R^2 of the corresponding regression study. The relative standard error (RSE) which is defined as the standard error (SE) when expressed as the percentage of the mean of the observed PM_{10} values can be used for comparing the applicability of a model for different sets of data. Therefore, in the validation studies, *RSE* of the regression stage was also compared with that of the validation stage (Chitranshi et al. 2014).

All the above models when developed can estimate hourly PM_{10} concentration twice a day at any ground pixel corresponding to the Terra and Aqua MODIS overpass. The average of these two hourly PM_{10} observations can be correlated with the observed daily mean PM_{10} concentration. This correlative model can thus facilitate the estimation of the daily mean PM_{10} concentration with the help of the estimated hourly PM_{10} concentrations as above.

5 Results

5.1 Descriptive statistics

Table 1 contained the annual means, μ (±1 standard deviation, σ) and the data count, n of PM_{10} (μg/m^3) and AOD_{MODIS} (dimensionless) for the three cities based on the data available for the years 2010–2012. While deducing the statistics for hourly PM_{10} measurements corresponding to the MODIS overpass, the data of the Kanpur City for the period before October 2010 and the data of Agra City for the monsoon period could not be included due to its non-availability in that year AOD_{MODIS} and PM_{10} data for the monsoon period were also scantly available in the study area. The annual mean AOD_{MODIS} in the region varied from 0.69 (±0.35) to 0.84 (±0.22) with the minimum in Agra City in the year 2010 and the maximum in Varanasi City in the year 2012. In general, AOD_{MODIS} values did not show any significant inter-annual variation during the study period. On the other hand, the regional means of AOD_{MODIS} were observed as 0.62 ± 0.13, 0.64 ± 0.27 and 0.84 ± 0.31 for the year 2010, 2011 and 2012, respectively. Figure 2a shows the seasonal variations of AOD_{MODIS} for the three cities. The AOD_{MODIS} was observed as the lowest in the winter as 0.43 (±0.19) and highest in the pre-monsoon/monsoon season as 1.27 (±0.33). These findings were also supported by Singh et al. (2004), Poarch et al. (2007), Ramachandran et al. (2012) and Choudhry et al. (2012).

The annual mean of hourly PM_{10} concentration was almost same for the years 2010 and 2011 but became relatively high in the year 2012 for all the three cities (Table 1). However, PM_{10} concentrations at Kanpur and Varanasi cities were higher than that at the Agra City. This feature was mainly attributed to the location of AAQMS. The differently placed locations of the monitoring stations are likely to affect the spatial variations in the estimators substantially. The regional mean PM_{10} values (average of the hourly PM_{10} values of the three cities) for the years 2010, 2011 and 2012 were found as 197.76 (±52.68), 179.67 (±80.12) and 239.86 (±86.76), respectively. Figure 2b shows the variations in the seasonal mean of PM_{10} ($\mu \pm \sigma$) concentration in the three

Table 1 Descriptive statistics of PM_{10} and AOD_{MODIS} at Agra, Kanpur and Varanasi cities for the years 2010, 2011 and 2012

City	2010		2011		2012	
	PM_{10} (μg/m^3)	AOD_{MODIS}	PM_{10} (μg/m^3)	AOD_{MODIS}	PM_{10} (μg/m^3)	AOD_{MODIS}
Agra	65.41 ± 33.66, 59	0.69 ± 0.35, 59	69.99 ± 30.78, 95	0.71 ± 0.36, 95	119.36 ± 46.59, 86	0.78 ± 0.28, 86
Kanpur	174.10 ± 48.22, 29	0.70 ± 0.29, 29	168.97 ± 54.12, 103	0.73 ± 0.27, 103	226.41 ± 42.86, 97	0.80 ± 0.29, 97
Varanasi	201.92 ± 67.61, 88	0.73 ± 0.26, 88	201.93 ± 89.24, 127	0.72 ± 0.23, 127	253.56 ± 74.31, 85	0.84 ± 0.22, 85
Regional mean	197.76 ± 52.68, 24	0.62 ± 0.13, 24	179.67 ± 80.12, 57	0.64 ± 0.27, 57	239.86 ± 86.76, 19	0.84 ± 0.31, 19

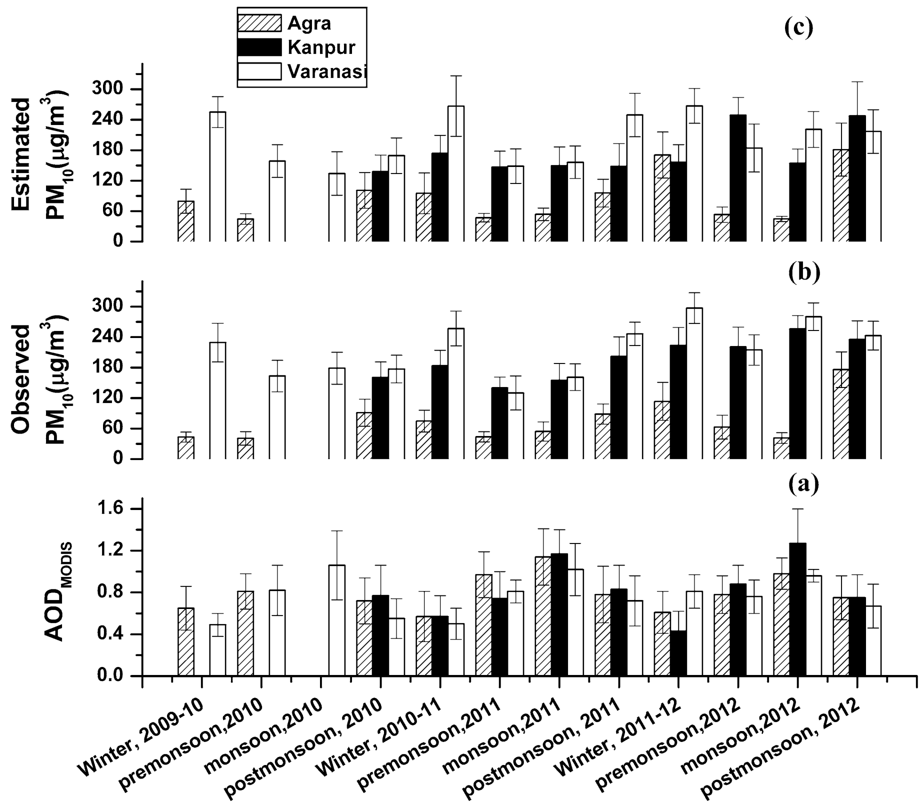

Fig. 2 Seasonal variations of **a** AOD_{MODIS}, **b** observed PM_{10} and **c** estimated PM_{10} in the study area for the years 2010, 2011 and 2012

cities. It was observed that Varanasi City had higher seasonal means than that of the other two cities. However, the highest concentration of PM_{10} was witnessed in the winter season and the lowest in the pre-monsoon.

A study of diurnal variation of hourly PM_{10} concentration is sometimes important as it can be used in identifying the periods of the day during which the pollution level exceeds the standard limit. This can help in managing the health impact of the particulate pollution. The diurnal variation of hourly PM_{10} values is not expected to vary significantly within a season. Average diurnal variations of PM_{10} during the four seasons of the year are plotted in Fig. 3. These plots indicated PM_{10} concentration in all the seasons peaked twice a day except in the monsoon season. The first peak occurred between 8 and 10 a.m. and the second peak between 8 and 10 p.m. The monsoon season did not witness any remarkable peak possibly due to turbulent and unstable weather conditions. Further, the daily mean PM_{10} concentration is more relevant than the hourly PM_{10} values, whereas the regression models proposed in this study intended to estimate only hourly PM_{10} concentrations at the ground monitoring sites coincidental to Terra and Aqua overpass time. Therefore, a correlative study between the average of these two overpass PM_{10} observations and the corresponding daily mean PM_{10} observations was done for each of the four seasons. The R^2 for winter, pre-monsoon, monsoon and post-monsoon seasons

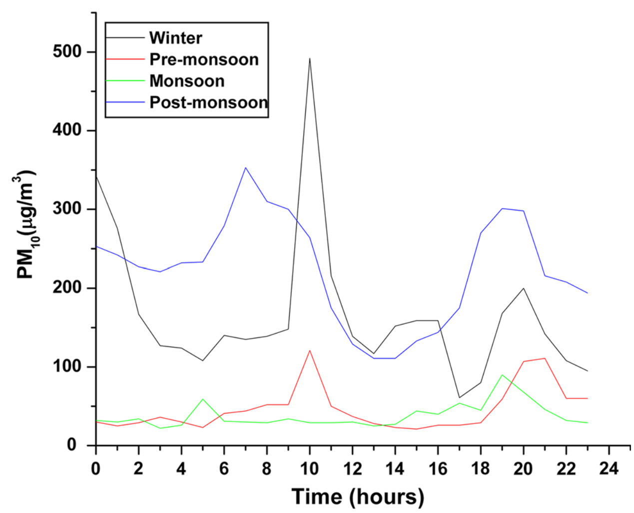

Fig. 3 Average diurnal variations of PM_{10} for four seasons a year

were found as 0.67, 0.41, 0.08 and 0.76, respectively. Here, it is observed that the correlation was good in winter and in post-monsoon seasons, whereas the monsoon season witnessed the poorest correlation and the pre-monsoon season witnessed the moderate one. This may be because of extremely turbulent weather conditions in north India prevailing in these two seasons and also due to the poor data availability in the monsoon season.

5.2 Modeling results

All the regression estimators, i.e., α (=124.75), β_1 (=244.53), β_2 (=1.18), β_3 (=−3.48) and β_4 (=−4.51) of the MRM which was developed using 81 regional mean observations were found to be significant ($p < 0.05$). The R^2 was found to be a moderate one ($\sim$0.59, $p < 0.05$) and the *RSE* of PM_{10} estimates was found to be 28.21 %. Subsequently, 81 data sets used for developing the MRM were split into 47 and 34 data sets corresponding to the Terra and the Aqua overpass, respectively, to develop separately the MRM_T and MRM_A models for the given region. R^2 of these two models were found as 0.63 and 0.47, respectively. The RDM was developed using 501 data sets pooled from all the three monitoring sites to estimate PM_{10} concentration at any given ground pixel in the region. A less moderate correlation ($R^2 = 0.37$, $p < 0.01$) was observed for this model. Although, all the regression estimators of this model were found to be significant ($p < 0.05$), they were able to explain only 37 % of the variability in the observed PM_{10} values (i.e., R^2). A relatively higher value of the RSE ($\sim$43 %) was observed for the RDM estimates. The statistical results of all the regional models have been summarized in Table 2.

Scatter plots of residual errors against PM_{10} values estimated by the MRM and the RDM are shown in Fig. 4. The scatter plot for MRM seems to follow a mild divergent trend, whereas that for the RDM showed a clear divergent trend. These trends indicated the possibility of further improvement in the model forms. The validation R^2 and RSE values for the MRM were found as 0.63 and 25 %, whereas those for the RDM were found as 0.45 and 40 %, respectively. These validation results for both these regional models were in conformity with the regression results. The aforesaid deficiencies in the MRM and RDM indicated the inadequacy of the proposed models for the satisfactory estimation of the PM_{10}. However, the results indicated the performance of the MRM as better than that of the RDM and MRM_A but inferior to MRM_T. Finally, the results suggest that the development of better forms of the models would be helpful. This model improvement was proposed using possible variations of the estimators temporally and also spatially across the region. The models incorporating these variations were studied in steps and the modeling results are presented below.

As discussed in the modeling approach, CMs for Kanpur and Varanasi cities were developed using 132 and 215 data sets, respectively. The results of CM for Agra City have been adopted from Chitranshi et al. (2014). The statistical results of all these models have been summarily presented in Table 2. The best correlation was found for the Varanasi CM ($R^2 = 0.68$) compared to Kanpur CM ($R^2 = 0.61$) and Agra CM ($R^2 = 0.56$). The RSE values were accordingly observed as 22.8, 33.23 and 54.58 %, respectively. All the city models and their estimators were found to be significant ($p < 0.05$). The estimators had a definite positive

Table 2 Regression results of regional models, city models and seasonal models

Model type	Data sets	Statistical parameter						
		R^2 for Reg./Val.	RSE (%) for Reg./Val.	α (sig)	β_1 (sig)	β_2 (sig)	β_3 (sig)	β_4 (sig)
Regional model								
MRM	81	0.59/0.63	28.21/25.45	124.75 (0.04)	244.53 (0.01)	1.18 (0.03)	−3.48 (0.05)	−4.51 (0.01)
MRM_T	47	0.63/0.65	25.33/22.57	170.24 (0.02)	255.06 (0.01)	0.87 (0.002)	1.19 (0.00)	−5.61 (0.02)
MRM_A	34	0.47/0.42	35.83/39.45	47.67 (0.00)	207.73 (0.01)	1.86 (0.04)	5.37 (0.02)	−2.36 (0.00)
RDM	501	0.37/0.45	43.67/40.43	122.75 (0.00)	170.79 (0.00)	1.10 (0.04)	−17.61 (0.03)	−1.92 (0.01)
City model								
[a]Agra	154	0.56/0.52	54.58/46.91	131.60 (0.04)	130.42 (0.00)	0.74 (0.03)	−10.80 (0.01)	−4.01 (0.00)
Kanpur	132	0.61/0.58	33.23/31.37	183.75 (0.00)	153.77 (0.00)	1.16 (0.06)	−1.91 (0.00)	−4.38 (0.00)
Varanasi	215	0.68/0.63	22.80/18.27	143.21 (0.00)	237.50 (0.00)	0.82 (0.004)	1.18 (0.06)	−4.05 (0.00)
Seasonal model								
Winter	155	0.51/0.61	31.23/33.62	−26.14 (0.01)	288.53 (0.00)	2.62 (0.002)	−9.25 (0.07)	6.85 (0.00)
Pre-monsoon	155	0.40/0.49	36.83/35.85	336.38 (0.00)	−52.42 (0.09)	−2.00 (0.007)	−13.97 (0.00)	−3.77 (0.01)
Monsoon	40	0.44/0.52	33.93/32.96	40.17 (0.08)	−60.79 (0.06)	−1.35 (0.002)	−15.04 (0.03)	−4.45 (0.04)
Post-monsoon	151	0.60/0.64	32.53/28.71	−02.79 (0.001)	273.95 (0.00)	2.54 (0.00)	−10.06 (0.00)	5.45 (0.00)

Reg. regression, *Val.* validation

[a] Results for Agra City are adopted from Chitranshi et al. (2014)

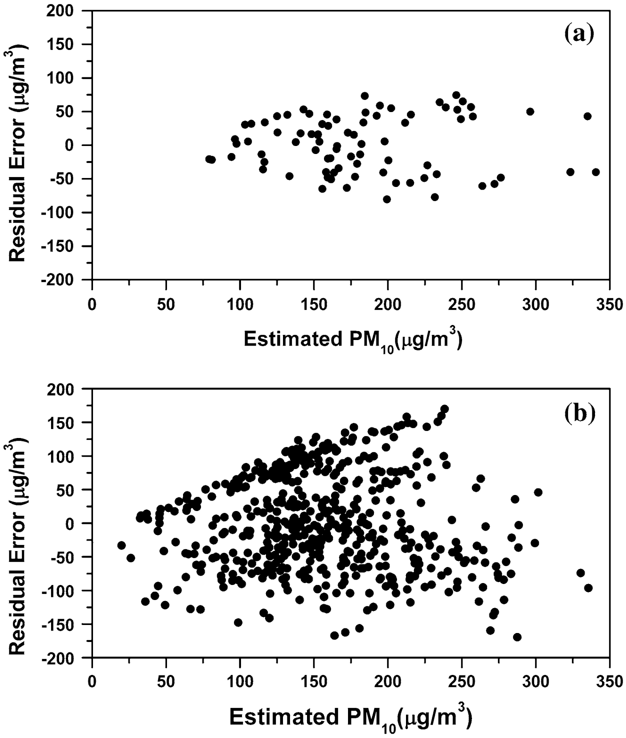

Fig. 4 Residual error plots for regional models estimated PM_{10} values for **a** 81 data pairs for MRM and **b** 501 data pairs for RDM collected during the years 2010 and 2011

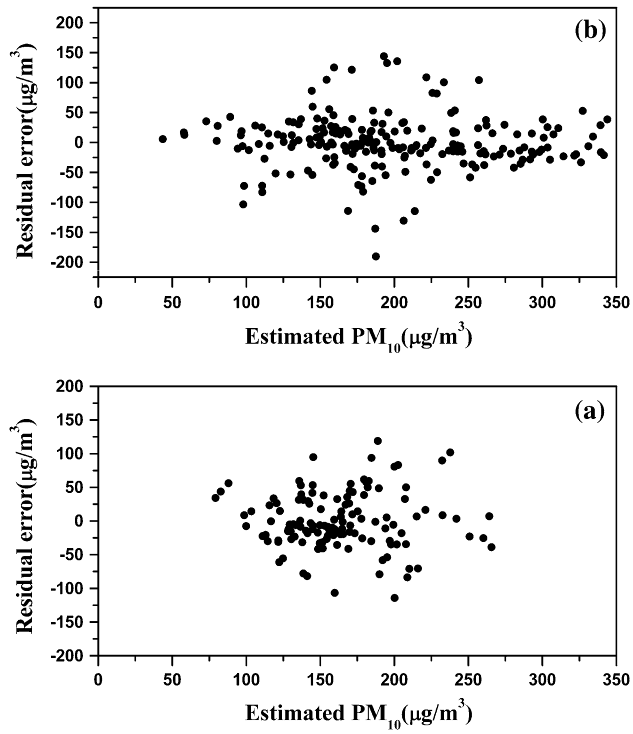

Fig. 5 Residual error plots for city models estimated PM_{10} values for **a** 132 data pairs at Kanpur and **b** 215 data pairs at Varanasi collected during the years 2010 and 2011

trend in their variations while moving from Agra to Varanasi. The residuals scatter plots of these two CMs (Fig. 5) were not confined to horizontal bands and rather followed oval-shaped trends. This suggested some possibilities of further improvement in the model forms. The validation results of these models were found similar to those of the regression results. The correlative performance of these models was slightly better than that of the MRMs.

The SMs for four seasons a year, i.e., winter, pre-monsoon, monsoon and post-monsoon were developed using 155, 155, 40 and 151 data sets, respectively. The statistical results of these models (Table 2) indicated better correlation for the SMs for the winter and post-monsoon seasons ($R^2 = 0.51$ and 0.60) than those for the pre-monsoon and monsoon seasons ($R^2 = 0.40$ and 0.43). The seasonal variation in the SMs' estimators did not show any specific trend. However, similarities have been observed between the estimators of the post-monsoon and winter SMs and between the estimators of the pre-monsoon and monsoon SMs. The residual scatter plots of these four SMs (Fig. 6) indicated the model adequacy for SMs for winter and post-monsoon seasons, but the SMs for pre-monsoon and monsoon seasons required further transformation in the model forms. Here also the validation results are close to the regression results. The overall performance of these SMs is slightly inferior to that of the CMs.

The concept of CSMs was based on the presumption that the regression estimators had both spatial as well as seasonal variations significantly within the given region. Therefore, the CSMs for all the four seasons for each of the three cities were developed by pooling the data sets seasonwise separately for each city. Table 3 contains the values of R^2, RSE, and all the estimators for all the 12 seasonal models and also the values of R^2 and RSE for the validation studies. The level of significance for each of the estimator has been provided in the parenthesis just below the value of the estimator itself.

From the close perusal of the regression results, it was observed that R^2 of CSMs for Agra City varied from 0.54 to 0.88 ($p \le 0.05$). The level of significance of all the estimators was found to be satisfactory ($p \le 0.05$). The *RSE* of regression estimates for these seasons varied from 17.2 to 30.2 %. Figure 7 contains the residual errors plotted against the estimated PM_{10} values for Agra City for all the four seasonal models. These residual error plots were found to be confined to almost horizontal bands suggesting the adequacy of the developed regression models. The R^2 and *RSE* of the validation studies of these models were also found in the vicinity of those of the regression results.

The results presented in Table 3 also showed all the seasonal models of the Kanpur City had a good correlation ($R^2 > 0.6$) except the pre-monsoon CSM which had a

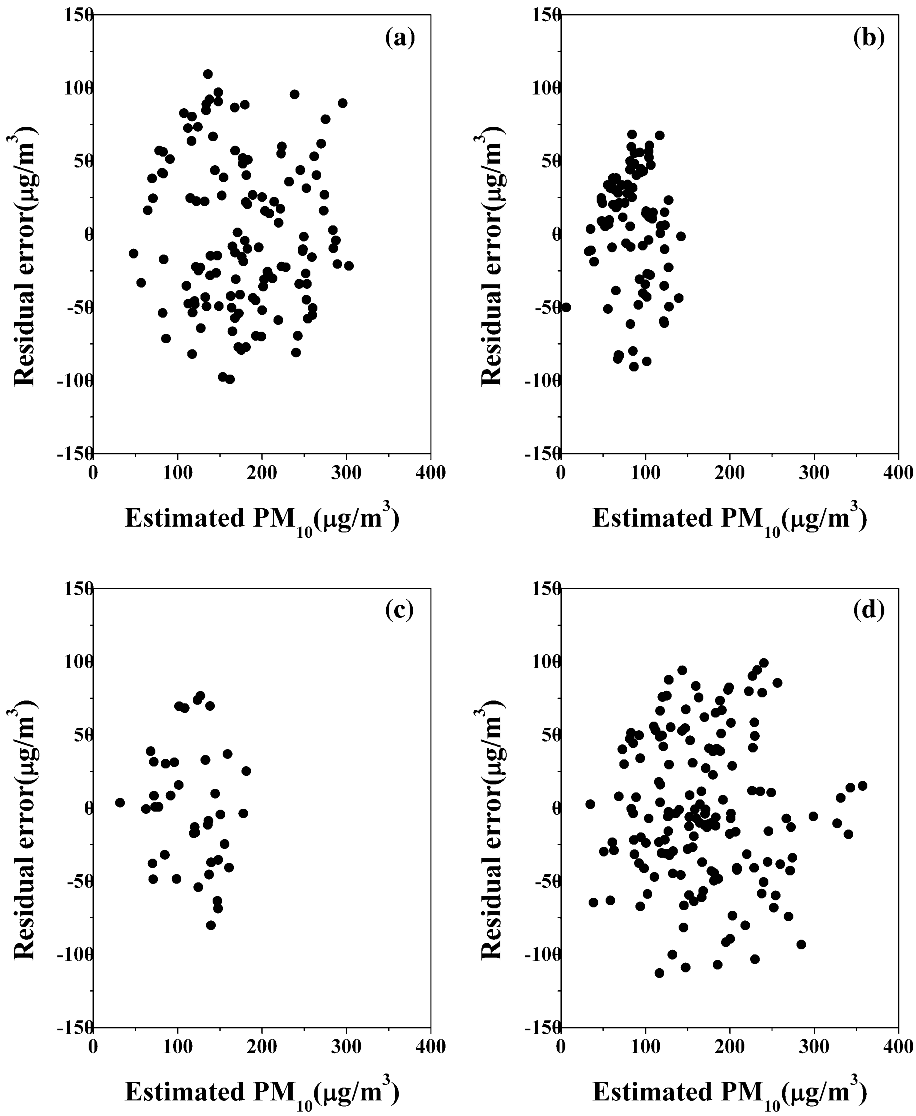

Fig. 6 Residual error plots for seasonal models estimated PM_{10} values for **a** 155 data pairs for winter, **b** 155 data pairs for pre-monsoon, **c** 40 data pairs for monsoon and **d** 151 data pairs for post-monsoon collected during the years 2010 and 2011

moderate correlation ($R^2 = 0.49$). The levels of significance of all the CSMs were less than 0.05. The RSE values for all the seasonal models were found less than 33 %. The residual error plots for the seasonal models of Kanpur City are shown in Fig. 8. These scatter plots were also found to be confined to almost horizontal bands and thus suggested the adequacy of these models for the desired estimation. The results of the validation studies also showed good correlation ($R^2 > 0.71$) for all the seasonal models except the pre-monsoon season which had moderate correlation ($R^2 = 0.51$). The low *RSE* values ($\leq$21 %) were found for all the seasonal models thus indicating a satisfactory model test results.

The CSMs for Varanasi City were able to explain about 60–86 % of the variability (R^2) significantly ($p \leq 0.05$) and had moderate *RSE* values ($\leq$34 %). Here also the residual error plots (Fig. 9) were confined to almost horizontal bands and thus suggesting the adequacy of the seasonal models of Varanasi City. The validation R^2 varied from 0.70 to 0.90 and *RSE* were found to be less than 13.4 % for these CSMs and thus suggesting the acceptability of these models for the estimation of PM_{10} in and around the Varanasi City area.

Figure 2c shows the variation in the seasonal means of hourly PM_{10} concentrations estimated by CSMs for the regression period (2010–2011) and for the validation period (2012). A satisfactory matching between this variation and the corresponding variation of the observed PM_{10} in Fig. 2b was observed except in the pre-monsoon and monsoon seasons of the year 2012. This may be due to poor correlation of CSMs for pre-monsoon and monsoon seasons.

Here, it is important to mention that the PM_{10} values estimated through any of the above models shall always be

Table 3 Regression results of city-wise seasonal models

City	Seasons	Data sets	Statistical parameter						
			R^2 for Reg./Val.	RSE (%) for Reg./Val.	α (sig)	β_1 (sig)	β_2 (sig)	β_3 (sig)	β_4 (sig)
Agra	Winter	50	0.88/0.74	25.3/28.3	39 (0.03)	204.24 (0.00)	1.97 (0.02)	−3.97 (0.03)	0.26 (0.04)
	Pre-monsoon	41	0.54/0.82	30.2/29.0	22 (0.001)	160.25 (0.00)	1.69 (0.03)	−7.37 (0.03)	0.51 (0.002)
	Monsoon	14	0.83/0.78	17.2/31.8	17.86 (0.01)	125.07 (0.00)	1.60 (0.00)	−2.32 (0.02)	0.43 (0.03)
	Post-monsoon	49	0.72/0.82	20.9/19.3	52 (0.02)	236.43 (0.00)	1.78 (0.00)	−1.62 (0.00)	1.2 (0.02)
Kanpur	winter	33	0.80/0.71	22.9/12.5	32 (0.00)	196 (0.03)	2.57 (0.03)	−4.03 (0.04)	0.37 (0.05)
	Pre-monsoon	40	0.49/0.51	32.9/21.0	24 (0.02)	147 (0.00)	1.39 (0.007)	−8.31 (0.04)	0.42 (0.007)
	Monsoon	13	0.63/0.76	17.3/18.8	15.02 (0.05)	117.05 (0.01)	1.47 (0.06)	−4.32 (0.008)	0.52 (0.03)
	Post-monsoon	46	0.76/0.84	22.6/12.9	49 (0.06)	214.40 (0.00)	1.69 (0.06)	−1.92 (0.05)	1.4 (0.05)
Varanasi	Winter	72	0.86/0.90	16.6/9.2	29 (0.03)	200 (0.00)	2.03 (0.01)	−5.25 (0.05)	0.32 (0.00)
	Pre-monsoon	74	0.61/0.70	32.3/13.4	21 (0.08)	141 (0.00)	1.19 (0.02)	−9.31 (0.03)	0.37 (0.04)
	Monsoon	13	0.76/0.81	33.9/12.1	14.09 (0.04)	115.37 (0.00)	1.39 (0.01)	−4.02 (0.00)	0.61 (0.009)
	Post-monsoon	56	0.72/0.79	12.6/8.0	47 (0.009)	192.25 (0.00)	1.59 (0.03)	−1.98 (0.02)	1.2 (0.008)

Reg. regression, *Val.* validation

associated with some estimation error due to the error of measurements/retrievals of the regressors, specially the AOD_{MODIS}. The estimation error of PM_{10} (i.e., ΔPM_{10} or improved estimation of PM_{10} − model estimated PM_{10}) due to the retrieval bias of AOD_{MODIS} can be simply computed by multiplying the AOD retrieval bias (i.e., ΔAOD_{MODIS} or $AOD_{AERONET} - AOD_{MODIS}$) by β_1. For example, if estimation of PM_{10} for Kanpur City is to be improved in the winter season, then using the estimator for AOD in the corresponding CSM (i.e., $\beta_1 = 196$ from Table 3) and the error envelop given by Levy et al. (2010), the estimation error of PM_{10} and its improved estimation can be written as:

$$\Delta\, PM_{10} = \pm 196 \times (0.05 + 0.15\, AOD_{MODIS}) \tag{5}$$

and

$$\text{Impoved estimation of } PM_{10} = \text{Estimated } PM_{10} \pm 196\ (0.05 + 0.15\, AOD_{MODIS}) \tag{6}$$

where the AOD_{MODIS} pertains to the Kanpur site in winter season.

6 Discussion and conclusions

In the present study, models based on the four approaches of multi-linear regression modeling were developed for estimating the PM_{10} in the central IGP using AOD_{MODIS} and the meteorological parameters as regressors. In the first approach, four types of regional models, i.e., MRM, MRM_T, MRM_A and RDM were developed which were able to estimate the PM_{10} at any time in the entire region. The first three regional models were able to estimate the mean regional PM_{10} concentration while the fourth one, i.e., RDM was able to estimate PM_{10} concentration at any specific AOD pixel in the region. The statistical performance of the MRM_T was found to be the best ($R^2 = 0.63$) while that of the RDM was the poorest ($R^2 = 0.37$) among all the regional models. The adequacy checks of these regional models suggested the transformation in the model forms. The CMs and SMs incorporated the spatial variations and the seasonal variations in the estimators, respectively. The CMs showed better correlation than those of the regional models. Although the pre-monsoon SM had poor correlation, the results of SMs of remaining seasons were slightly better ($R^2 = 0.40$–0.68) than those of the regional models but slightly inferior to those of the CMs. The scatter plots of CMs and SMs also indicated the need for further improvement. The CSMs were able to incorporate the spatial and temporal variations together in the estimators. The results of CSMs were found to be better as compared to the regional models, CMs and SMs. The scatter plots also showed them as adequate enough to estimate PM_{10} satisfactorily. The best correlation was observed in the winter seasonal models of all the cities ($R^2 = 0.80$–0.88) and the weakest was observed in the

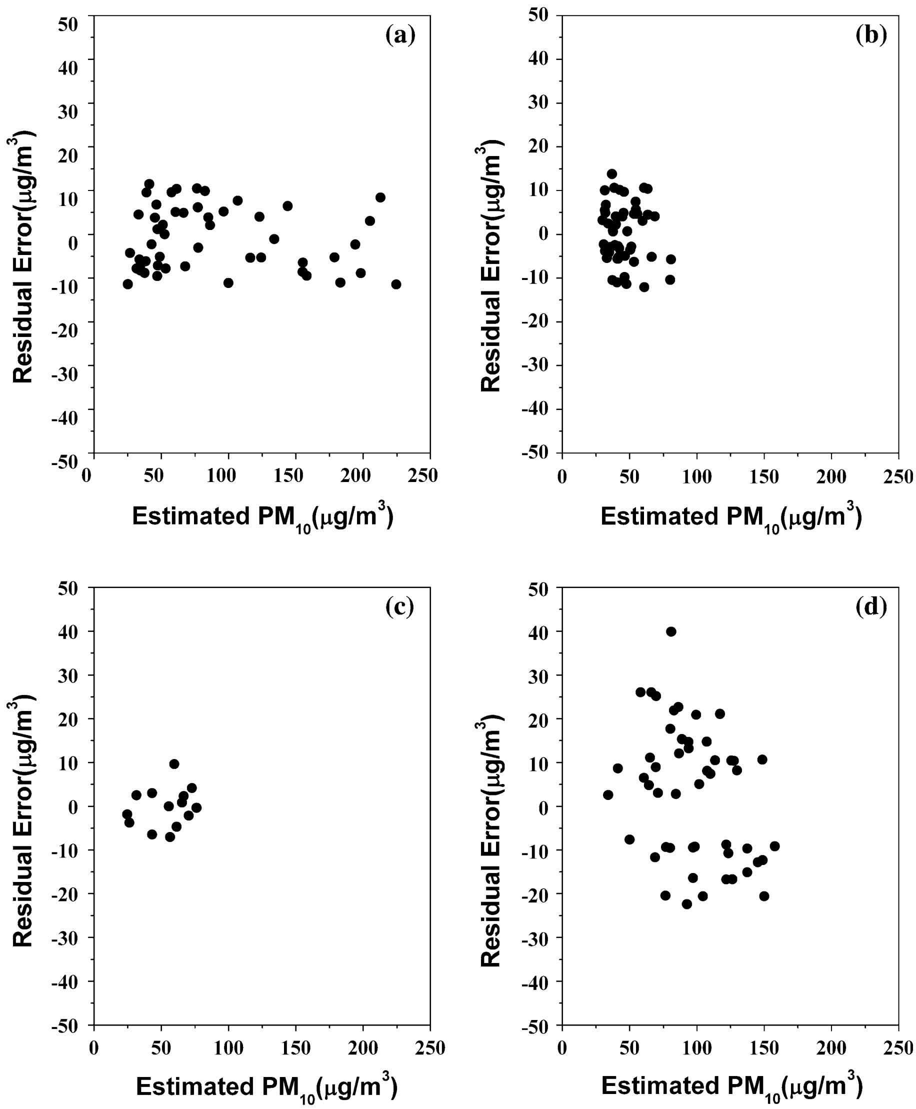

Fig. 7 Residual error plots for city-wise seasonal models estimated PM_{10} values at Agra City for **a** 50 data pairs for winter, **b** 41 data pairs for pre-monsoon, **c** 14 data pairs for monsoon and **d** 49 data pairs for post-monsoon collected during the years 2010 and 2011

pre-monsoon seasonal models ($R^2 = 0.47$–0.61). This finding is similar: (a) to the findings of the correlative study between the mean of the two overpass PM_{10} values and its daily mean where the correlation was found poor/moderate in monsoon and in pre-monsoon seasons; and (b) to the findings of seasonal modeling where the correlation of monsoon and pre-monsoon SMs was found to be unsatisfactory. This poor correlation in pre-monsoon season is attributed to the fact that the extreme turbulent weather conditions including occasional dust storms prevail in north India during this season resulting in a huge aerosol loading at higher altitudes, i.e., 2–5 km (Dipu et al. 2013 and Kaskaoutis et al. 2013). This phenomenon increases the AOD_{MODIS} level substantially without influencing much the ground level PM_{10} concentration. More remarkable variation in the regression estimators was observed temporally than spatially. The spatial variation in the estimators was observed from 1.2 times to 1.5 times, whereas the temporal variation was observed from 2 to 4 times As has been mentioned earlier also, these variations were attributed to the land use, climatology and anthropogenic activities responsible for the particulate pollution and also the placing of the AAQMS with respect to the nearby hot spots. It was also observed that the sign (+ or −) and the order of magnitude of the estimators were more or less same for CSMs of all the cities for a particular season. The negative sign associated with WS estimator (i.e., β_3) indicated the lower PM_{10} concentration at higher wind speed which has also been found by Liu et al. (2006). They also found that the higher AT accelerated the generation of secondary particles near the ground surface, causing a higher proportion of particle mass in the mixed layer, which would explain the positive estimator of the AT.

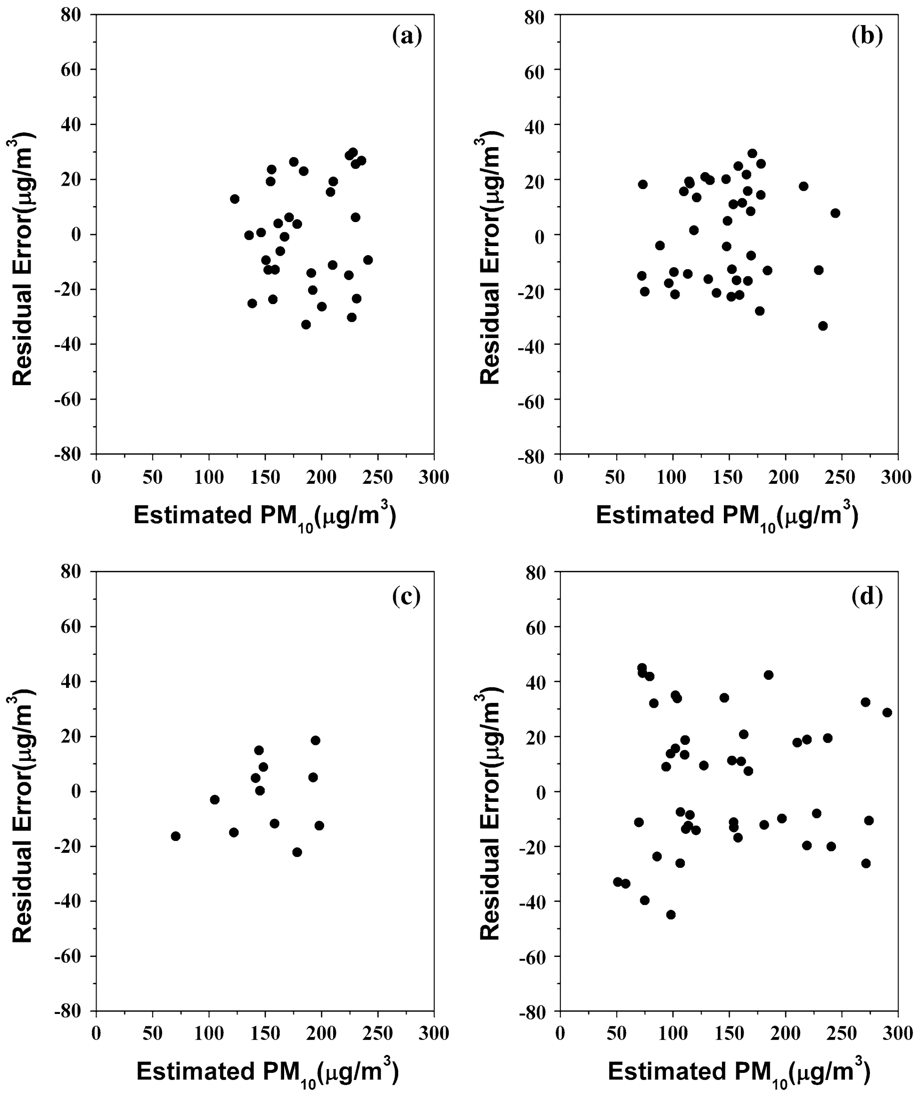

Fig. 8 Residual error plots for city-wise seasonal models estimated PM_{10} values at Kanpur City for **a** 50 data pairs for winter, **b** 41 data pairs for pre-monsoon, **c** 14 data pairs for monsoon and **d** 49 data pairs for post-monsoon collected during the years 2010 and 2011

The particulate pollution represents the aerosol loading in the mixing height or boundary/mixed layer due to the anthropogenic activities and some natural reasons. Whereas the AOD represents the aerosol loading in the entire atmospheric column including that in the boundary layer. Therefore, to obtain a high correlation between AOD and PM, the spatio-temporal variations in the particulate loading in the boundary layer must be associated either with almost similar or no spatio-temporal variations in the aerosols loading in the background atmosphere (i.e., the entire atmospheric column excluding the boundary layer). If the spatio-temporal variations in the aerosol loading in these two segments of the atmospheric column are significant but dissimilar, the said correlation is bound to be poor. Therefore, the AOD-PM correlation could be improved by incorporating other factors influencing the AOD/PM loading such as climatic factors, local conditions and seasonal factors. The climatic/seasonal factors predominantly affect the aerosol loading in the northern India and especially IGP (Kaskaoutis et al. 2013). The present study has attempted to take care of this aspect best by developing the seasonal models for each individual city, i.e., CSMs. However, the seasonal and/or climatic factors may be taken care in a better way if monthly models are developed instead of seasonal models subject to the availability of sufficient monthly data. Further, reducing the error of measurements/retrievals will help greatly in refining the models. More number of ground monitoring stations in a city will always be desirable to have a more representative PM concentration of the city.

The PM_{10} and the meteorological parameters were measured at a single point in the city, whereas the AOD_{MODIS} was deduced as the average value of the pixel

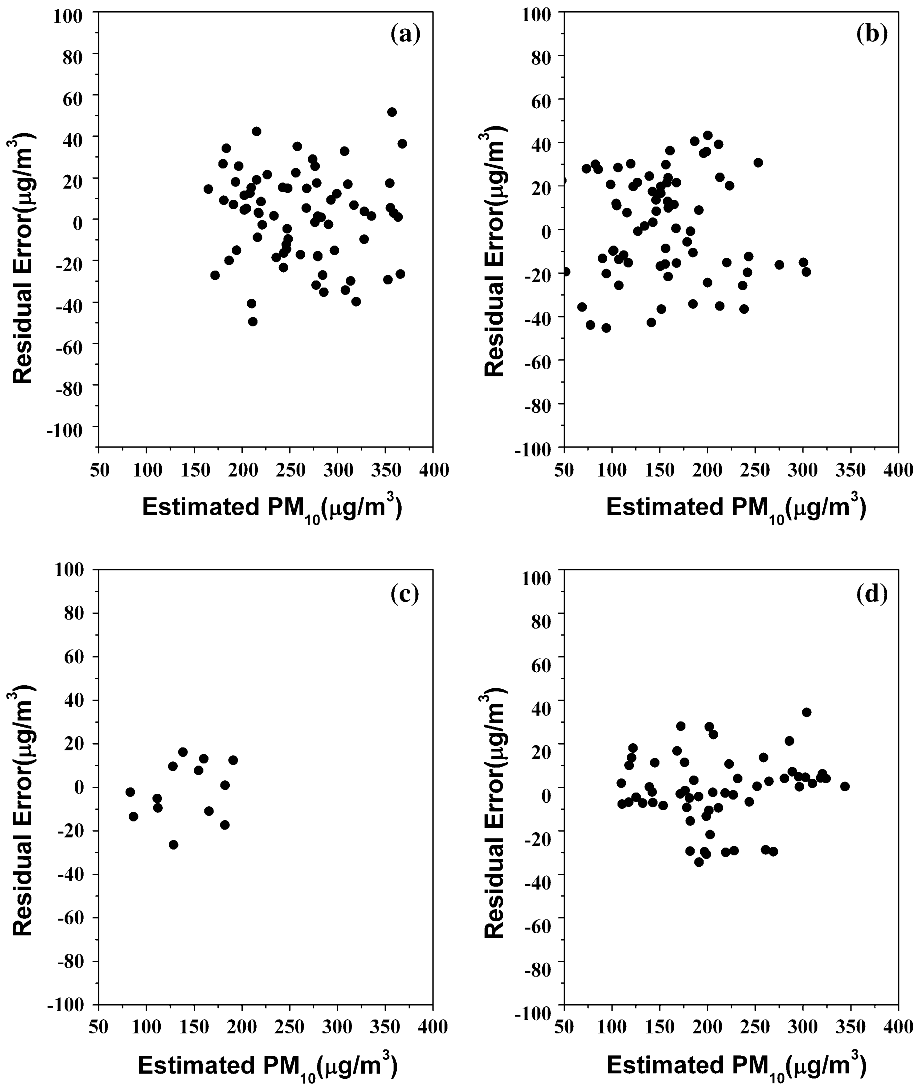

Fig. 9 Residual error plots for city-wise seasonal models estimated PM_{10} values at Varanasi City for **a** 50 data pairs for winter, **b** 41 data pairs for pre-monsoon, **c** 14 data pairs for monsoon and **d** 49 data pairs for post-monsoon collected during the years 2010 and 2011

(10 × 10 km) covering the ground monitoring station. It is, therefore, not appropriate to expect a very high reproducibility in the regional estimates of PM_{10}. For reliable estimation of PM_{10} in any city of the central IGP, one may develop the seasonal models of that city in a similar manner and thus PM_{10} concentrations can be estimated in a cost-effective manner as the satellite data are readily available. Thus, the proposed CSMs can reliably generate regional maps for the PM_{10} covering most of the cities of UP in the central IGP taking into account the spatio-temporal variations in the estimators. The results reported in this study can also be used to estimate PM_{10} profiles (surfaces) of the study area for the previous years as well. As the urban air quality has been deteriorating year by year affecting the health and quality of life of the people of these cities, the present study can be of immense help in the development of better satellite-based health management strategies. Finally, it is important to note that the direct extrapolation of the results from this study to other regions may not be possible without further analysis.

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