Surface PM$_{2.5}$ Estimate Using Satellite-Derived Aerosol Optical Depth over India

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ABSTRACT

Concentrations of fine particulate matter (PM$_{2.5}$) that exceed air quality standards affect human health and have an impact on the earth’s radiation budget. The lack of round the clock ground-based observations from a dense network of air quality stations inhibits the understanding of PM$_{2.5}$’s spatio-temporal variability and the assessment of its health and climate effects. Aerosol optical depth (AOD) values retrieved from satellite based instruments can be used to derive surface PM$_{2.5}$ concentrations. This study integrates Moderate Resolution Imaging Spectroradiometer (MODIS) AOD retrievals and simulations from the Weather Research and Forecasting Model coupled with Chemistry (WRF-Chem) to determine the ground-level PM$_{2.5}$ concentrations at a 36 km resolution across India. WRF-Chem simulations provide the factor relating the AOD with the PM$_{2.5}$. Satellite-derived PM$_{2.5}$ mass concentrations are compared with the available ground-based observations across India for the year of 2011. The results show a correlation between the satellite-derived monthly PM$_{2.5}$ estimates and the ground-based observations for 15 stations in India with coefficients of 77% and diurnal scale coefficients varying from 0.45 to 0.75. The best estimations of PM$_{2.5}$ mass concentrations on a spatio-temporal scale across India address various environmental issues.

Keywords: AOD; PM$_{2.5}$; Spatio-temporal variability of PM$_{2.5}$; Impact assessment.

INTRODUCTION

Mass concentration of fine particulate matter (PM$_{2.5}$) frequently exceeds beyond its air quality standards in most of the megacities in the South Asia which attracted attention of researchers for its environmental impact assessments (Li et al., 2015; Chowdhury and Dey, 2016; Chew et al., 2016; Ghude et al., 2016), regional air quality (Tiwari et al., 2012; Ali et al., 2013; Trivedi et al., 2014; Apte, 2015; Ghude et al., 2016; Parkhi et al., 2016; Srinivas et al., 2016; Balasubramanian et al., 2017) and climatic effects (Lin et al., 2013; Stocker et al., 2013; Tiwari et al., 2015; Gupta et al., 2006) including visibility during fog episodes (Ghude et al., 2017). PM$_{2.5}$ emits from the variety of sources and shows good correlations with the ambient concentrations of sulphate, ammonium, nitrate, sea salt, carbonaceous aerosols, and dust particles. The rapid economic development, in conjunction with increased transportation activity and energy consumption, PM$_{2.5}$ pollution is an important environmental problem in India (Lelieveld et al., 2001; Badarinath et al., 2010).

Few studies have examined PM$_{2.5}$ distribution due to man-made aerosols emissions (Pillai et al., 2002; Latha et al., 2005; Kulshrestha et al., 2009; Bala Krishna et al., 2011; Gummeneni et al., 2011; Tiwari et al., 2012b, 2013; Deshmukhet al., 2013; Su et al., 2014; Yadav et al., 2014; Balasubramanian et al., 2017) in India. The ground-based in-situ monitoring networks provide the most accurate measurements of PM$_{2.5}$ but these point measurements are generally representative of local conditions and scattered in space and time which makes it difficult to use them in the assessment of regional scale variability (Ghude et al., 2016). Measurement of aerosol optical depth (AOD) from satellite platform provides an alternative tool to assess the ground-level PM$_{2.5}$ concentrations at regional and global scale but their application requires derivation of relationships between AOD and PM$_{2.5}$ (Hoff and Christopher, 2009; Van Donkelaar et al., 2010; Reis et al., 2015; Chew et al., 2016; Zheng et al., 2016; Bilal et al., 2017; Yeganeh et al., 2017).

Several studies have investigated quantitative relationship between satellite-derived AOD and ground-level PM$_{2.5}$ measurements using numerous methods. Most of the studies have used simple empirical observation based methods (Wang and Christopher, 2003; Engel-Cox et al., 2004; Schaap et al., 2009; Lin et al., 2014; Li et al., 2015) that...
rely on the relationship between air quality measurements and different observations (Maciejewska et al., 2015). Some investigations often have used the local meteorological information to better relate AOD and PM$_{2.5}$ (Liu et al., 2005; Gupta et al., 2006; Koelmeijer et al., 2006). Locally derived AOD-PM$_{2.5}$ relationships cannot be extended easily to other regions because of aerosol sources and a wide range of weather conditions associated with the regional geography (Schaap et al., 2009). Local time-dependent AOD-PM$_{2.5}$ relationships are necessary to derive regional estimates of PM$_{2.5}$. However, ground-based measurements of aerosol vertical profiles and properties often suffer from insufficient coverage to estimate regional and PM$_{2.5}$ relationships. Advanced method such as simple regression (Chu et al., 2003); multiple regression (Dirgawati et al., 2015; Gupta and Christopher, 2009); generalised additive models (Liu et al., 2009); geographically weighted regression (Ma et al., 2014) and semi-empirical model (Koelmeijer et al., 2006) have been used to accurately represent the relationship between AOD and surface PM$_{2.5}$ concentration.

As an alternative to statistical models, predicting ground-level PM$_{2.5}$ using numerical-based models that includes dispersion, chemistry and meteorology has also been shown to produce reasonable results (Liu et al., 2004; Gupta et al., 2006; Van Donkelaar et al., 2006, 2010; Li et al., 2015; Bilal et al., 2017). These studies build a local relationship between AOD and PM$_{2.5}$ mass concentrations at every model grid point by taking advantage of aerosol profile information from chemical transport models (van Donkelaar et al., 2006, 2010; Kessner et al., 2013). Using this method one can reasonably estimate ground-level PM$_{2.5}$ concentrations in regions without monitoring sites at a resolution of tens to hundreds of kilometers. These results are limited by uncertainties due to emission inventories, chemical and dynamical processes of aerosols in the atmosphere (Chate and Devara, 2005; Kondragunta et al., 2008; Gupta and Christopher, 2009; Chate and Murugvel, 2010; Lin et al., 2015).

Liu et al. (2004) developed a simple, yet effective approach to estimate the surface PM$_{2.5}$ concentrations by applying local scaling factors to AOD retrieved from MODIS from a global atmospheric chemistry model. In this study, we followed Liu et al. (2004) approach and estimated the local scaling factor for each MODIS pixel using PM$_{2.5}$ and AOD simulations from the regional chemical transport model WRF-Chem. We then apply this relationship to each MODIS AOD retrieval to backtrack the surface PM$_{2.5}$ concentrations for India. We aim to develop a satellite-based estimate of ground-level PM$_{2.5}$ at a spatial resolution of 36 km. We further, validate derived PM$_{2.5}$ against the ground-based observational datasets from different sampling locations collected under Modelling Air Pollution and Networking (MAPAN) project, and also against various published research articles in India. The location of these observation sites is shown in Fig. 1.

By integrating the MODIS AOD retrievals with the WRF-Chem model, we derive a satellite-based estimate of monthly mean surface PM$_{2.5}$ at a spatial resolution of 36 ×

![Fig. 1. Observational sites (Daily and monthly) all over India.](image)
36 km² for entire India for the year 2011. Satellite-derived surface PM₂.₅ concentrations are compared with the National Ambient Air Quality Standard for PM₂.₅ to identify the regions that exceed the safety limit set by the government. Rest of the manuscript is organized as follows. Section 2 provides details of the materials and methods used in this study. The spatial and temporal variability in satellite-derived PM₂.₅ estimates is discussed and evaluated in Section 3 and summarized in Section 4.

**MATERIALS AND METHODS**

**Estimating PM₂.₅ from Satellite AOD**

The MODIS instrument aboard the Terra and Aqua satellite measures aerosol optical depth (AOD) at 550 nm with a wide range of spatial information and provides near-daily global coverage (Levy *et al.*, 2007). Terra satellite crosses the equator at 10:30 local solar time. Here we used MODIS Terra Level 2, Collection 5 (C5) Dark Target (DT) aerosol retrievals at 10 km resolution, available from the Goddard Earth Sciences Data Information Service Center (https://modis-atmos.gsfc.nasa.gov/products.html). MODIS operational C5 retrievals employ two algorithms for retrieving aerosol properties over land and oceans: the Dark Target (DT) algorithm over land, the DT algorithm over ocean and the Deep Blue (DB) algorithm over land. A MODIS cloud mask with 99% cloud free criteria is used to filter out the cloudy pixels.

The regional simulations for the entire year 2011 in this study are conducted using the WRF-Chem version 3.6.1 driven by NCEP/FNL meteorological reanalysis fields (GFS/NFL). The simulations were run at a spatial resolution of 36 × 36 km² covering South Asia (0–40°N to 60–120°E) and 27 vertical levels from surface up to 50 hPa with chemical initial and boundary fields from MOZART-4 (Emmons *et al.*, 2010), anthropogenic emissions from Hemispheric Transport of Air Pollution (HTAP-v2), fire emissions from Fire INventory from NCAR (FINNv1) and biogenic emissions from Model of Emissions of Gases and Aerosols from Nature (MEGAN) (Guenther *et al.*, 2006). Model for Ozone and Related Chemical Tracers (MOZART-4) gas-phase chemistry linked to the Goddard Chemistry Aerosol Radiation and Transport (GOCART) aerosol scheme solves for the temporal and spatial evolution of gaseous compounds and aerosols such as sulfate, ammonium, BC, OC, mineral dust, and sea salt. Summary of entire model setup is given in Table 1.

Satellite derived ground-level PM₂.₅ concentration (EPM₂.₅) can be inferred from the total column AOD retrieved from the satellite instruments using a conversion factor that accounts for their spatio-temporal variability, using the following relationship:

\[ E_{PM\_2.5} = \xi \times \text{AOD} \]  

where, \( \xi = M_{PM\_2.5}/M_{AOD} \)

MPM₂.₅ represents the modeled simulated surface PM₂.₅ concentration, \( M_{AOD} \) the total column AOD simulated from the model and AOD is satellite observed aerosol optical depth. Here the ratio (\( M_{PM\_2.5}/M_{AOD} \)) is a function of the factors that relate satellite observations of AOD with aerosol mass which consider the aerosol type, aerosol size, relative humidity, vertical profile, diurnal variation from van Donkelaar *et al.* (2006). This method has also been used in several previous studies (e.g., Liu *et al.*, 2004; van Donkelaar *et al.*, 2006; Liu *et al.*, 2007). The aerosol optical properties in WRF-Chem are calculated at 300, 400, 600 and 999 nm. To derive \( M_{AOD} \) at 550 nm, the Angström power law is used:

\[ \lambda / \Gamma(\lambda_O) = (\lambda / \lambda_O)^\alpha \]  

where \( W(\lambda) \) is the model AOD at wavelength \( \lambda \) (550 nm) and \( \alpha \) is the Angström exponent calculated from model AOD at 400 and 600 nm using the following relation:

\[ \alpha = \frac{\ln \left( \frac{W(400)}{W(600)} \right)}{\ln \left( \frac{600}{400} \right)} \]  

**Table 1. WRF-Chem configuration.**

<table>
<thead>
<tr>
<th>Atmospheric process</th>
<th>Model configuration</th>
</tr>
</thead>
<tbody>
<tr>
<td>Surface layer</td>
<td>Noah Land Surface Model (Chen and Dudhia, 2001)</td>
</tr>
<tr>
<td>Radiation</td>
<td>LW: RRTM (Mlawer <em>et al.</em>, 1997)</td>
</tr>
<tr>
<td></td>
<td>SW: Goddard (Chou and Suarez, 1994)</td>
</tr>
<tr>
<td>Cumulus</td>
<td>Grell 3D Cumulus Parameterization scheme (Grell <em>et al.</em>, 2002)</td>
</tr>
<tr>
<td>Planetary boundary layer</td>
<td>Bougeault and Lacarrere Planetary Boundary Layer (PBL) scheme (Bougeault and Lacarrere, 1989)</td>
</tr>
<tr>
<td>Microphysics</td>
<td>Thompson scheme (Thompson <em>et al.</em>, 2008)</td>
</tr>
<tr>
<td>Gas-phase chemistry</td>
<td>MOZART-4</td>
</tr>
<tr>
<td>Aerosol chemistry</td>
<td>GOCART</td>
</tr>
<tr>
<td>Photolysis</td>
<td>Madronich F-TUV (Madronich <em>et al.</em>, 1987)</td>
</tr>
<tr>
<td>Biogenic emissions</td>
<td>Megan (Guenther <em>et al.</em>, 2006)</td>
</tr>
<tr>
<td>Fire emissions</td>
<td>NCAR version-1 (FINNv1) (Wiedinmyer <em>et al.</em>, 2011)</td>
</tr>
<tr>
<td>Dry deposition</td>
<td>Wesely (1989)</td>
</tr>
<tr>
<td>Wet deposition</td>
<td>Neu and Prather (2012)</td>
</tr>
</tbody>
</table>
Eqs. (2) and (3) are consistent with the WRF-Chem framework as the model also uses these equations for aerosol-radiation interaction in the model by interpolating/extrapolating the AOD (400–600 nm) to RRTM spectra (0.2–12 µm). For consistency with satellite retrievals, a model factor of the $\frac{M_{PM2.5}}{MAOD}$ ratio at each day is interpolated in time and space to the locations of valid satellite retrievals (pixel) using a bilinear interpolation of the four nearest model grid points. The co-located model and observed daily data are averaged to obtain a monthly mean value for each $36 \times 36$ km$^2$ grid box.

RESULTS AND DISCUSSIONS

The spatial distributions of annually averaged MODIS retrieved and WRF-Chem simulated AOD for the year 2011 over India at the temporally collocated satellite overpass time are shown in Figs. 2(a) and 2(b), respectively. Both observed and modeled data set exhibits similar spatial distribution over India at larger scales but there are visible differences at local scales. A large AOD enhancement over the industrial and densely populated regions, including the entire northern region of India (Indo-Gangetic Plain) and along the western and eastern coastline is clearly evident (Mhawish et al., 2017). Both data sets also show lower AOD values over the state of Rajasthan (or western India) and central India. A large enhancement in the MODIS retrievals appears to be consistent with troposphere NO$_2$ (Ghude et al., 2013a) and CO (Ghude et al., 2011; Surenderan et al., 2015) data sets, which reflects the influence of anthropogenic sources. The spatial discrepancy between MODIS retrieved and WRF-Chem simulated AOD over India is further illustrated by the satellite-model differences (Fig. 2(c)). In general, the model underestimates the MODIS AOD values particularly over the northern part of India by about 20–40%. The model also tends to underestimate AOD retrievals over southernmost part of India by about 10%. The observed discrepancies between simulated and observed tropospheric AOD are consistent with results from previous studies over India (Kumar et al., 2014). These differences point to general underestimation of anthropogenic emissions in the IGP (Nair et al., 2012; Kumar et al., 2014). Another possible source of difference can arise from errors in simulating dust emission and transport over this region. Kumar et al. (2014) found that WRF-Chem model significantly underestimates dust emissions over this region. On the other hand, model overestimates the MODIS AOD over the far eastern part of India and Burma by about 20–25%, where strong biomass burning occurs during pre-monsoon season. This suggests that FINNv1 aerosol emission from biomass burning may be too high in this region. Jena et al. (2014) have investigated the behavior of modeled concentration of NO$_x$ using the FINNv1 inventory for pre-monsoon season. Their study resulted in an overestimation of modeled NO$_x$ concentration by a factor of 2.2 over Burma region. However, over remaining part of India, the model shows very good agreement with the MODIS retrieved AOD.

The spatial variation of annual PM$_{2.5}$ concentration derived from MODIS AOD retrievals is consistent with the spatial distribution of MODIS AOD (Fig. 3). It shows high PM$_{2.5}$ concentration over the industrial or densely populated regions, including entire IGP and along the western and northern part of India.
eastern coastline. Emission sources, meteorology and special topography in the IGP region favors the development of high PM$_{2.5}$ values in this region. Fig. 3(a) reveals that over large parts of IGP region annual derived mean surface PM$_{2.5}$ concentrations can be as high as 150–180 µg m$^{-3}$, which suggest high PM$_{2.5}$ pollution in this region and vulnerability of population living in this part of the world to poor air quality. Spatial variation of seasonal mean estimated PM$_{2.5}$ concentration for pre-monsoon, monsoon, post-monsoon and winter seasons is shown in Figs. 3(b), 3(c), 3(d) and 3(e), respectively. It can be seen in Fig. 3 that MODIS algorithm is insufficient to capture the Aerosol Optical Depth over Himalayan mountain ranges (Chu et al., 2002) and therefore PM$_{2.5}$ estimate over this region could not be possible. In the pre-monsoon season (March–April–May), PM$_{2.5}$ concentration is high compared to monsoon season because of accumulation of aerosols in the atmosphere which is strongly influenced by regional loading due to the transport of dust outbreaks originated in the Thar Desert and the Arabian Peninsula (Gautam et al., 2009; Gautam et al., 2011). Due to valley like topography, pollutants get trapped largely over IGP region. In the monsoon season (June–July–August–September) we can clearly see that the PM$_{2.5}$ concentration is significantly less compared to other season. This can be attributed to wet removal of suspended particles due to rain (Seinfeld and Pandis, 2006; Gautam et al., 2011). In the winter months (December–January–February) PM$_{2.5}$ concentration is found to be highest because of stable atmospheric conditions, low boundary height and winter biomass burning (Ghude et al., 2013b; Jena et al., 2015) in this region that leads to accumulation of aerosols for longer time.

**PM$_{2.5}$ Validation**

**Comparison with Ground-Based Monitoring Station**

Satellite-derived ground-based PM$_{2.5}$ and WRF-Chem simulated surface PM$_{2.5}$ is evaluated against the monthly mean observations available at 15 stations across India (Fig. 1). It should be noted that derived PM$_{2.5}$ are for the year 2011 while data for the ground stations are for different years (Table 2). This is because of limited publicly available data for stations other than our own observational sites. Our objective is to investigate how well modeled and estimated PM$_{2.5}$ is able to capture the inter-annual variability. These observations are compiled by Ghude et al. (2016) and are a mixture of data from the MAPAN, observational network of the Ministry of Earth Sciences (MoES) and from the Indian Institute of Tropical Meteorology (IITM) and published by individual groups (Table 2). Local value of derived PM$_{2.5}$ in Eq. (1) is for MODIS (Terra) overpass times is around 10:30 LT. In order to compare monthly mean PM$_{2.5}$ with an estimate from satellite, we calculated monthly ratio ‘$\eta$’ from simulated monthly mean and values corresponding to satellite overpass times for each station location. We further apply $\eta$ to estimate PM$_{2.5}$ to get corrected monthly means estimate for each station shown in Fig. 1.

Comparison of monthly averaged satellite-derived surface PM$_{2.5}$ (red) and WRF-Chem simulated (blue) concentration with ground-based observations in India show that derived PM$_{2.5}$ show strong seasonal variation with a reasonable agreement with the observations (Fig. 4). For comparison we have selected pixels close to the observation site (around 10 km radius). Over most of the observation sites, derived PM$_{2.5}$ are found to vary between 20 and 150 µg m$^{-3}$, except at some sites in central and northern Indian like Delhi, Noida, Agra, Patiala, Raipur and Guwahati where it shows high variability up to 200–400 µg m$^{-3}$. It can be seen that predicted average values are maximum in winter and lowest in summer. This is consistent with the seasonal pattern of observed PM$_{2.5}$ over India. However, the evaluation may be interpreted with caution, since satellite derived PM$_{2.5}$ are for the year 2011 while data for the few ground stations are for different years as mentioned in Table 2. Compared to observations, predicted PM$_{2.5}$ shows higher concentrations during summer seasons, particularly over the sites located in the northern parts of India. Overall, the derived PM$_{2.5}$ overestimates the observed PM$_{2.5}$ concentrations over India, at all sites. It could be due to the fact that most of these observation sites are situated near the dense traffic areas and therefore influenced by local emissions that are not completely resolved by the model while deriving AOD-PM$_{2.5}$ relationship in Eq. (1). Overall, these results suggest that the derived PM$_{2.5}$ concentrations are a fair representation of the surface concentrations observed at the Indian monitoring sites.

It can seen from Figs. 4 and 5 derived PM$_{2.5}$ overestimates the mean values, particularly during summer (MJJA) and winter season (DJF) and it is pronounced over the sites situated in the northern region of India (e.g., Delhi, Noida, Patiala, Agra). Several factors can contribute to an overestimation of monthly averaged values. Active

<table>
<thead>
<tr>
<th>S. no</th>
<th>Lat and Lon</th>
<th>Data</th>
<th>Station</th>
<th>Data extract from various Publication</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>20.91°N, 82.00°E</td>
<td>Jul 2009–Jun 2010</td>
<td>Raipur</td>
<td>Dhashmukhet al., 2013</td>
</tr>
<tr>
<td>2</td>
<td>8.48°N, 76.95°E</td>
<td>Jan 1999–Dec 1999</td>
<td>Trivandrum</td>
<td>Pillai et al., 2002</td>
</tr>
<tr>
<td>3</td>
<td>21.21°N, 86.75°E</td>
<td>May 2006–Apr 2007</td>
<td>Anantapur</td>
<td>Balakrishnaiah et al., 2011</td>
</tr>
<tr>
<td>4</td>
<td>27.18°N, 78.02°E</td>
<td>Jan 2007–Dec 2007</td>
<td>Agra</td>
<td>Kulshrestha et al., 2009</td>
</tr>
<tr>
<td>5</td>
<td>24.58°N, 73.68°E</td>
<td>Jan 2011–Dec 2011</td>
<td>Udaipur</td>
<td>Yadav et al., 2014</td>
</tr>
<tr>
<td>6</td>
<td>17.28°N, 78.26°E</td>
<td>Jan 2003–Dec 2003</td>
<td>Hyderabad</td>
<td>Latha et al., 2005</td>
</tr>
<tr>
<td>7</td>
<td>17.28°N, 78.26°E</td>
<td>June 2004–May 2005</td>
<td>Hyderabad</td>
<td>Gummenehi et al., 2011</td>
</tr>
<tr>
<td>8</td>
<td>28.61°N, 77.20°E</td>
<td>Jan 2011–Dec 2011</td>
<td>Delhi</td>
<td>Tiwari et al., 2013</td>
</tr>
</tbody>
</table>
Fig. 4. Variability of monthly mean satellite-derived (red), model (blue) and observed (black) surface PM$_{2.5}$ (in μg m$^{-3}$) over 15 monitoring locations.

Fig. 5. Variability of monthly mean satellite derived surface PM$_{2.5}$ (red), satellite derived surface PM$_{2.5}$ (Blue) excluding the sites in northern region of India during summer months (MJJA), and observed (black) averaged from all 15 locations (representative of the mean seasonal cycle) over India.
spells of rainfall within the monsoon season reduce aerosol concentrations significantly via wet deposition while break spells lead to a buildup of aerosols and higher AOD (Manoj et al., 2012; Connolly et al., 2013; Latha et al., 2014). Therefore, mean observed concentration during monsoon season tend to be lower because of averaging over both active and break spells (Fig. 5). In contrast, PM$_{2.5}$ derivation from satellite AOD is attempted only for the clear sky conditions (cloud fraction > 50%) and thus satellite-derived PM$_{2.5}$ estimates are more representative of break spell aerosol loadings. Correlation between observed and satellite derived monthly mean PM$_{2.5}$ concentrations for all fifteen sites in India is shown in Fig. 6(a). Similarly, Fig. 6(b) shows correlation between observed and modeled monthly mean PM$_{2.5}$ concentrations for the same sites. It can be seen that compared to molded PM$_{2.5}$ concentrations ($r = 0.59$) the satellite derived PM$_{2.5}$ shows high temporal and spatial correlations ($r = 0.77$) with the observations. However, derived annual mean PM$_{2.5}$ is biased by $\sim$13 µg m$^{-3}$. Correlation between estimated and observed PM$_{2.5}$ in this study is found to be similar to the correlation observed in other studies over India (Kumar et al., 2007). Fig. 6(b) also suggests that model in general underestimate higher PM$_{2.5}$ values particularly, PM$_{2.5}$ concentration more than 120 µg m$^{-3}$.

During the winter season, the entire IGP region is covered with the haze. Due to topography like valleys, cold weather condition, biomass burning, dust lifting and high regional emissions, aerosols get trapped largely over the IGP region (Gautam et al., 2009). This can significantly affect the optical properties (Dey et al., 2004; Gautam et al., 2011). This combination forms a thick haze (Gautam et al., 2009) and persistent fog layer over the entire region (Ghude et al., 2017) and consequently, very high AOD values (Ramanathan and Ramana, 2005; Gautam et al., 2011; Ram et al., 2016) are seen over the entire IGP. Formation of haze and fog over the IGP is still difficult to reproduce in the regional models (Gao et al., 2015; Ghude et al., 2017; Gao et al., 2017). This highlights the difficulty to calculate the reliable value of $\xi$ in Eq. (1) over this region. Therefore, derived PM$_{2.5}$ during winter seasons reflects the overestimation over the sites located in the northern plain of India.

**Comparison and Temporal Variation of Daily Observations**

The ability of satellite-derived PM$_{2.5}$ concentrations to capture the observed variability at daily scale is examined by comparing the time series of derived and ground-level PM$_{2.5}$ for five stations (Delhi, Pune, Jabalpur, Hyderabad, and Udaipur) where daily surface measurements are available (Fig. 8). For this comparison, we have sampled hourly mean surface PM$_{2.5}$ data (10:00–11:00 LT) which is close to the MODIS (Terra) overpass times for which PM$_{2.5}$ mass concentrations are derived. In Fig. 8, surface observations of PM$_{2.5}$ are represented with red while derived PM$_{2.5}$ are superimposed with black. Satellite-derived PM$_{2.5}$ mass concentrations capture the observed temporal variability reasonably well at all the five sites with correlation coefficient ranging from 0.45 to 0.75 (Fig. 9). Among all the observational stations Delhi is highly correlated with the ground-level PM$_{2.5}$ whereas is Hyderabad and Udaipur are fewer correlation values (0.45). Correlation between observed and satellite derived daily mean PM$_{2.5}$ concentrations for all five sites in India is shown in Fig. 7. It can be seen that satellite derived PM$_{2.5}$ shows significant temporal correlation ($r = 0.68$) with the observations. We found that normalized mean bias between estimated and observed PM$_{2.5}$ was lowest in pre-monsoon season (+0.0028) showing highest accuracy for this season. Whereas, during monsoon, post-monsoon and winter season normalized mean bias was observed to be +0.178, +0.278 and $-0.2053$, respectively. These correlation coefficient values are comparable with the recent studies (Li et al., 2015; Chew et al., 2016; Berlusconi et al., 2016; Zhang et al., 2016; Zheng et al., 2016; Bilal et al., 2017) at other geographical locations.

**CONCLUSIONS**

The main goal of this study was to assess and establish a relationship between satellite retrieved AOD values and
Fig. 7. Scatter plot between observed Daily mean of 5 stations and satellite derived PM$_{2.5}$ (in µg m$^{-3}$) concentrations.

Fig. 8. Comparison between observed (red) and estimated (black) daily surface PM$_{2.5}$ concentration variation over Delhi, Pune, Jabalpur, Hyderabad, and Udaipur monitoring sites.
Fig. 9. Scatter plot values between observed and satellite derived PM$_{2.5}$ (in µg m$^{-3}$) concentrations over Delhi, Pune, Jabalpur, Hyderabad, and Udaipur.

the choice of aerosol model and to improved satellite retrieval. However, the current research can be a useful first-hand tool for policymakers for targeting potential polluted areas in India with control measures.

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