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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; Deshmukh*et 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

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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; Koelemeijer *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 ×

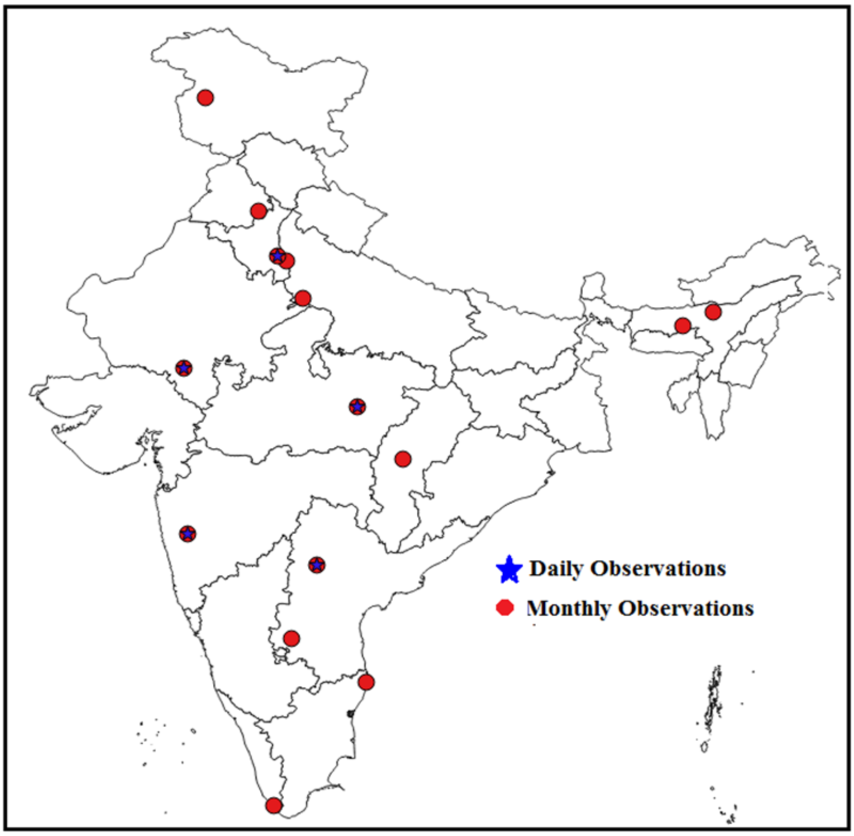

Fig. 1. Observational sites (Daily and monthly) all over India.

36 km^2 for entire India for the year 2011. Satellite-derived surface $PM_{2.5}$ concentrations are compared with the National Ambient Air Quality Standard for $PM_{2.5}$ 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 $PM_{2.5}$ estimates is discussed and evaluated in Section 3 and summarized in Section 4.

MATERIALS AND METHODS

Estimating $PM_{2.5}$ 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 km^2 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 $PM_{2.5}$ concentration ($E_{PM2.5}$) 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:

$$E_{PM2.5} = \xi \times AOD \quad (1)$$

where, $\xi = M_{PM2.5}/M_{AOD}$

$MPM_{2.5}$ represents the modeled simulated surface $PM_{2.5}$ concentration, M_{AOD} the total column AOD simulated from the model and AOD is satellite observed aerosol optical depth. Here the ratio ($M_{PM2.5}/M_{AOD}$) 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:

$$\Gamma\,\lambda/\Gamma\,\lambda_O = (\lambda/\lambda_O)^{-\alpha} \quad (2)$$

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

$$\alpha = \frac{\ln\left(\frac{W(400)}{W(600)}\right)}{\ln\left(\frac{600}{400}\right)} \quad (3)$$

Table 1. WRF-Chem configuration.

Atmospheric process	Model configuration
Surface layer	Noah Land Surface Model (Chen and Dudhia, 2001)
Radiation	LW: RRTM (Mlawer *et al.*, 1997) SW: Goddard (Chou and Suarez, 1994)
Cumulus	Grell 3D Cumulus Parameterization scheme (Grell *et al.*, 2002)
Planetary boundary layer	Bougeault and Lacarrere Planetary Boundary Layer (PBL) scheme (Bougeault and Lacarrere, 1989)
Microphysics	Thompson scheme (Thompson *et al.*, 2008)
Gas-phase chemistry	MOZART-4
Aerosol chemistry	GOCART
Photolysis	Madronich F-TUV (Madronich *et al.*, 1987)
Biogenic emissions	Megan (Guenther *et al.*, 2006)
Fire emissions	NCAR version-1 (FINNv1) (Wiedinmyer *et al.*, 2011)
Dry deposition	Wesely (1989)
Wet deposition	Neu and Prather (2012)

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 $M_{PM2.5}/M_{AOD}$ 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 × 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

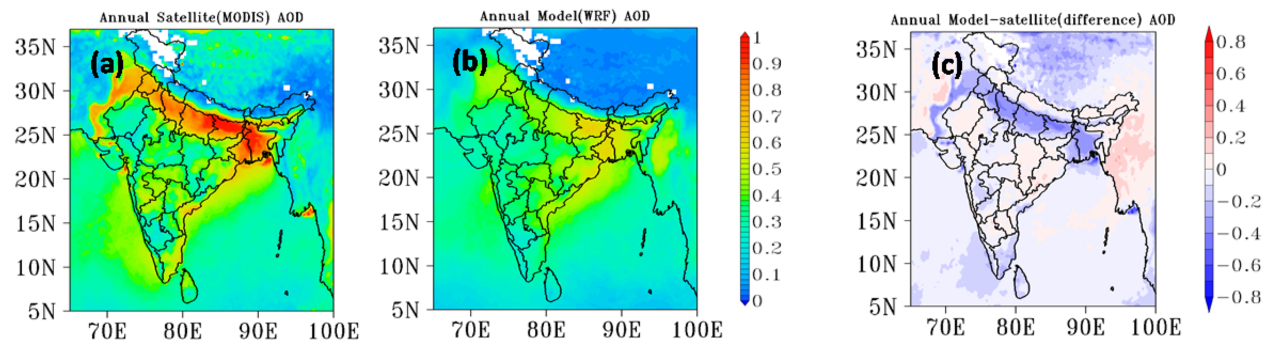

Fig. 2. Annual mean Aerosol Optical Depth (AOD) (a) MODIS Satellite, (b) WRF-Chem Model, and (c) annual model-satellite (difference).

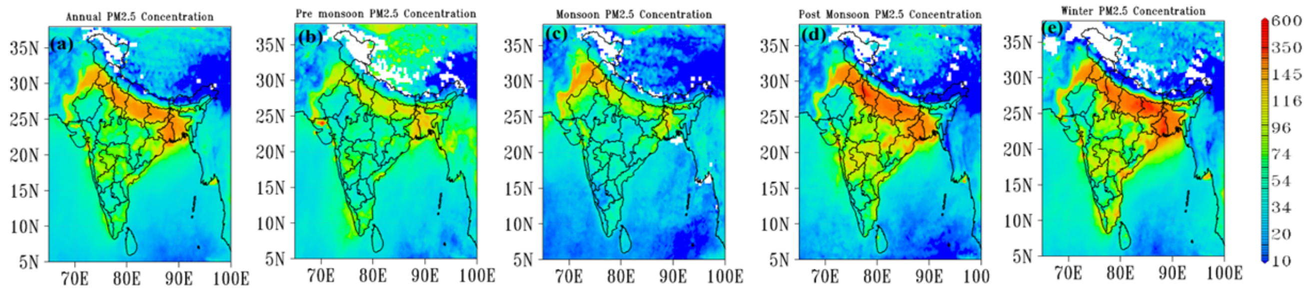

Fig. 3. (a) Annual and seasonal (b) Premonsoon, (c) Monsoon, (d) Post Monson, and (e) Winter mean $PM_{2.5}$ concentration (in µg m^{-3}) for the year 2011.

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 'ŋ' from simulated monthly mean and values corresponding to satellite overpass times for each station location. We further apply ŋ 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 2. Data used from other Stuides.

S. no	Lat and Lon	Data	Station	Data extract from various Publication
1	20.91°N, 82.00°E	Jul 2009–Jun 2010	Raipur	Deshmukh*et al.*, 2013
2	8.48°N, 76.95°E	Jan 1999–Dec 1999	Trivandrum	Pillai *et al.*, 2002
3	21.21°N, 86.75°E	May 2006–Apr 2007	Anantapur	Balakrishnaiah*et al.*, 2011
4	27.18°N, 78.02°E	Jan 2007–Dec 2007	Agra	Kulshrestha*et al.*, 2009
5	24.58°N, 73.68°E	Jan 2011–Dec 2011	Udaipur	Yadav *et al.*, 2014
6	17.28°N, 78.26°E	Jan 2003–Dec 2003	Hyderabad	Latha, *et al.*, 2005
7	17.28°N, 78.26°E	June 2004–May 2005	Hyderabad	Gummeneni *et al.*, 2011
8	28.61°N, 77.20°E	Jan 2011–Dec 2011	Delhi	Tiwari *et al.*, 2013
9	28.61°N, 77.20°E	Jan 2007–Dec 2009	Delhi	Tiwari*et al.*, 2012

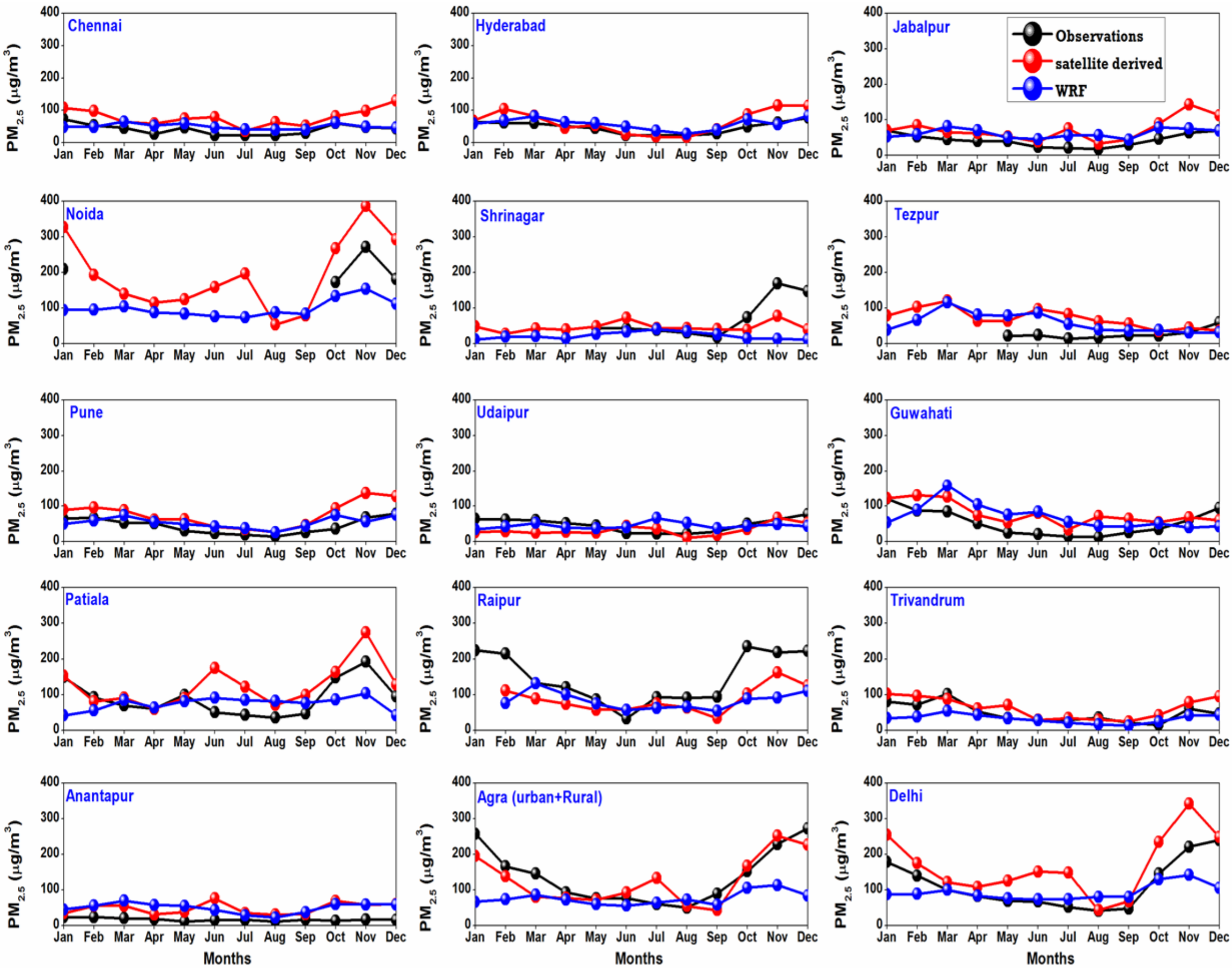

Fig. 4. Variability of monthly mean satellite-derived (red), model (blue) and observed (black) surface $PM_{2.5}$ (in μg m^{-3}) over 15 monitoring locations.

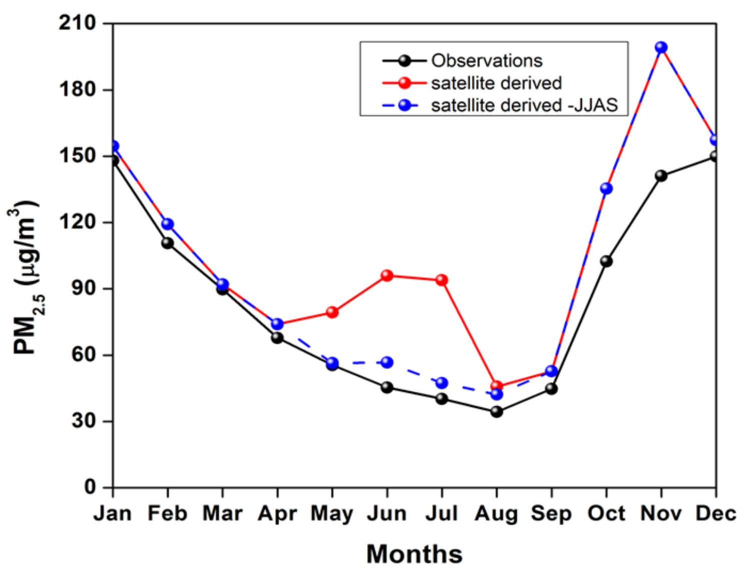

Fig. 5. Variability of monthly mean satellite derived surface $PM_{2.5}$ (red), satellite derived surface $PM_{2.5}$ (Blue) excluding the sites in northern region of India during summer months (MJJA), and observed (black) averaged from all 15 locations (representative of the mean seasonal cycle) over 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 ~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 'ξ' 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 station 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

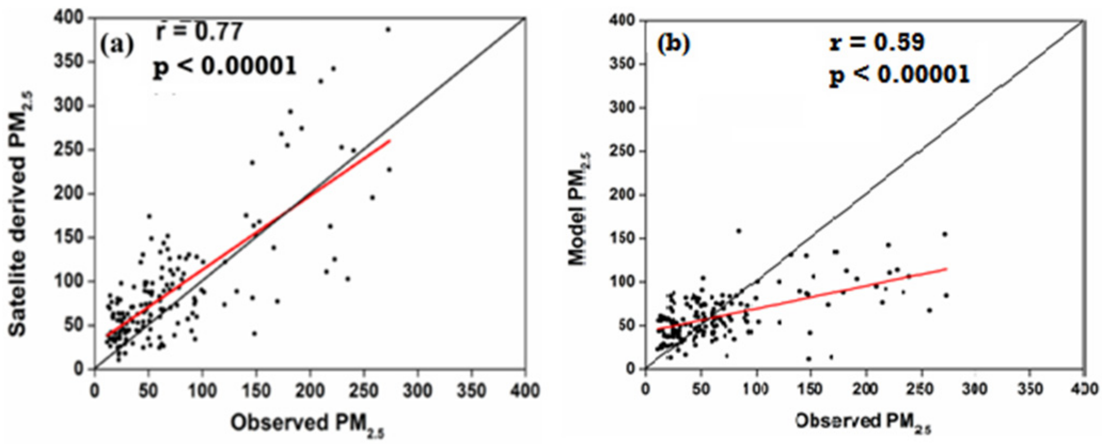

Fig. 6. Scatter plot between monthly (a) observed and derived $PM_{2.5}$ (in µg m^{-3}) concentrations and (b) observed and modeled $PM_{2.5}$ (in µg m^{-3}) concentrations for all 15 ground based observations.

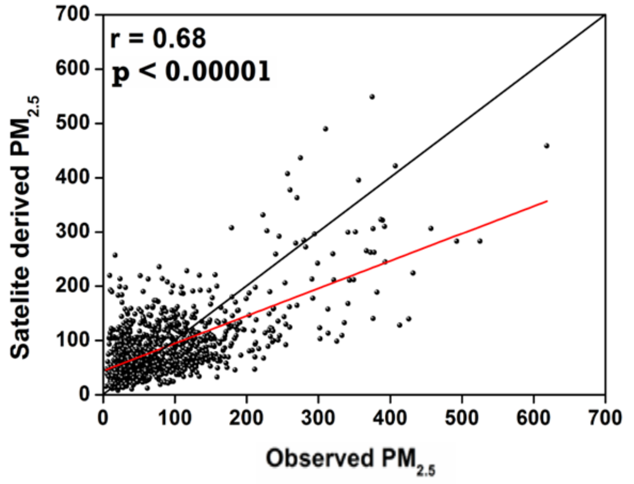

Fig. 7. Scatter plot between observed Daily mean of 5 stations and satellite derived $PM_{2.5}$ (in µg m^{-3}) concentrations.

the $PM_{2.5}$ over the Indian region in light of the limited spatial coverage of in-situ $PM_{2.5}$ measurements. We applied a satellite-model based inversion method to predict ground-level $PM_{2.5}$ concentrations. MODIS Terra retrieved AOD measurements and regional chemical transport model (WRF-Chem) simulations were employed to derive the surface $PM_{2.5}$ concentration for the period of January to December 2011 for a 36 km grid resolution. The derived $PM_{2.5}$ concentrations show high seasonal variation and reasonably agree with the mean monthly surface observations from different geographical locations in India. The derived concentration was found to vary between 20 and 150 µg m^{-3}, except at some sites in central and northern India, such as Delhi, Noida, Agra, Patiala, Raipur and Guwahati, where it exhibited high variability and maximums up to 200–400 µg m^{-3}. The discrepancies between the derived and the observed concentrations could be due to the fact that most of the observation sites are situated near dense traffic areas and therefore influenced by local emissions that are not completely resolved by the model in deriving the AOD-$PM_{2.5}$ relationship. Daily variation in the predicted surface $PM_{2.5}$ levels generally displayed better agreement with in situ measurements from the individual urban clusters of the Delhi area, Pune, Jabalpur, Hyderabad and Udaipur, with correlation coefficients of 0.75, 0.68, 0.55, 0.45 and 0.45, respectively. This work suggests the feasibility of using satellite measurements of AOD over India to derive useful information on surface $PM_{2.5}$ concentrations when combined with a priori information from a regional chemical transport model. However, these results are limited by uncertainties due to emission inventories, chemical and dynamical processes of aerosols in the atmosphere (Kumar *et al.*, 2018), and errors in satellite retrieval. With the MODIS C5 algorithm, the use of static surface databases limits the algorithm's ability to retrieve aerosol values over regions with seasonal vegetation changes. Also, the retrievals were only performed over bright-reflective surfaces, leading to insufficient information for retrievals over regions with mixed vegetative and non-vegetative surfaces (Hsu *et al.*, 2013). Additional constraints on the recently available high-resolution satellite data (Collection 6 and Collection 6.1) products might allow for more accurate derived concentrations of $PM_{2.5}$, particularly over urban regions (Mhawish *et al.*, 2017; Bilal *et al.*, 2018; Gupta *et al.*, 2018). Future studies should explore the sensitivity of derived $PM_{2.5}$ concentrations to

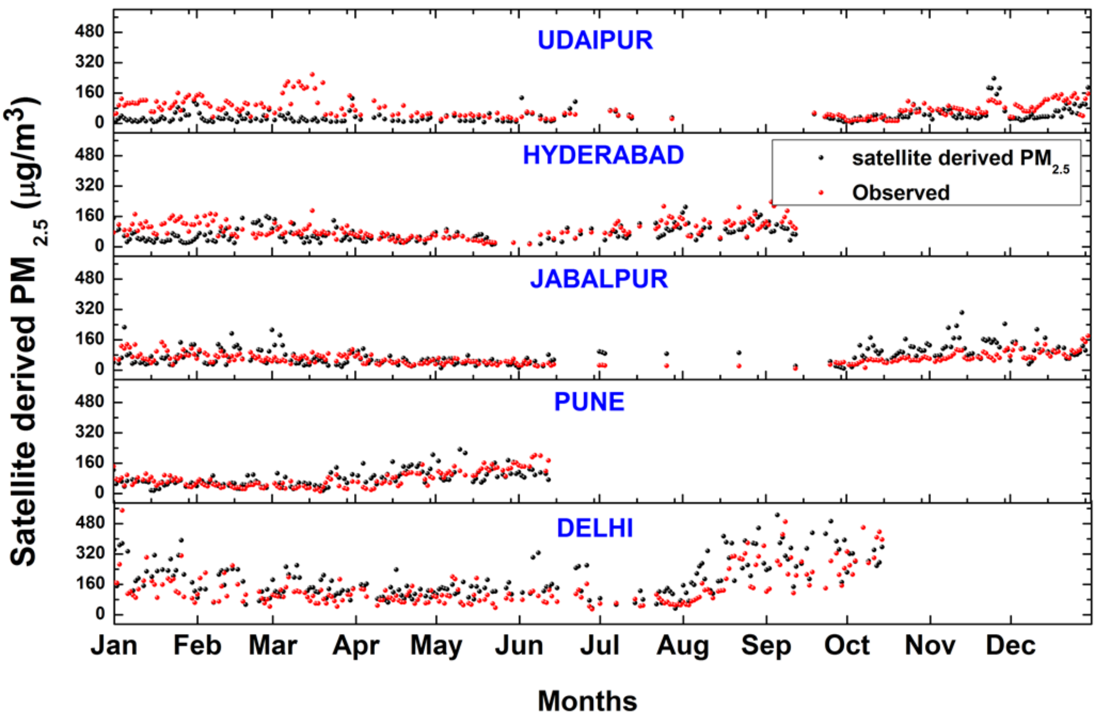

Fig. 8. Comparison between observed (red) and estimated (black) daily surface $PM_{2.5}$ concentration variation over Delhi, Pune, Jabalpur, Hyderabad, and Udaipur monitoring sites.

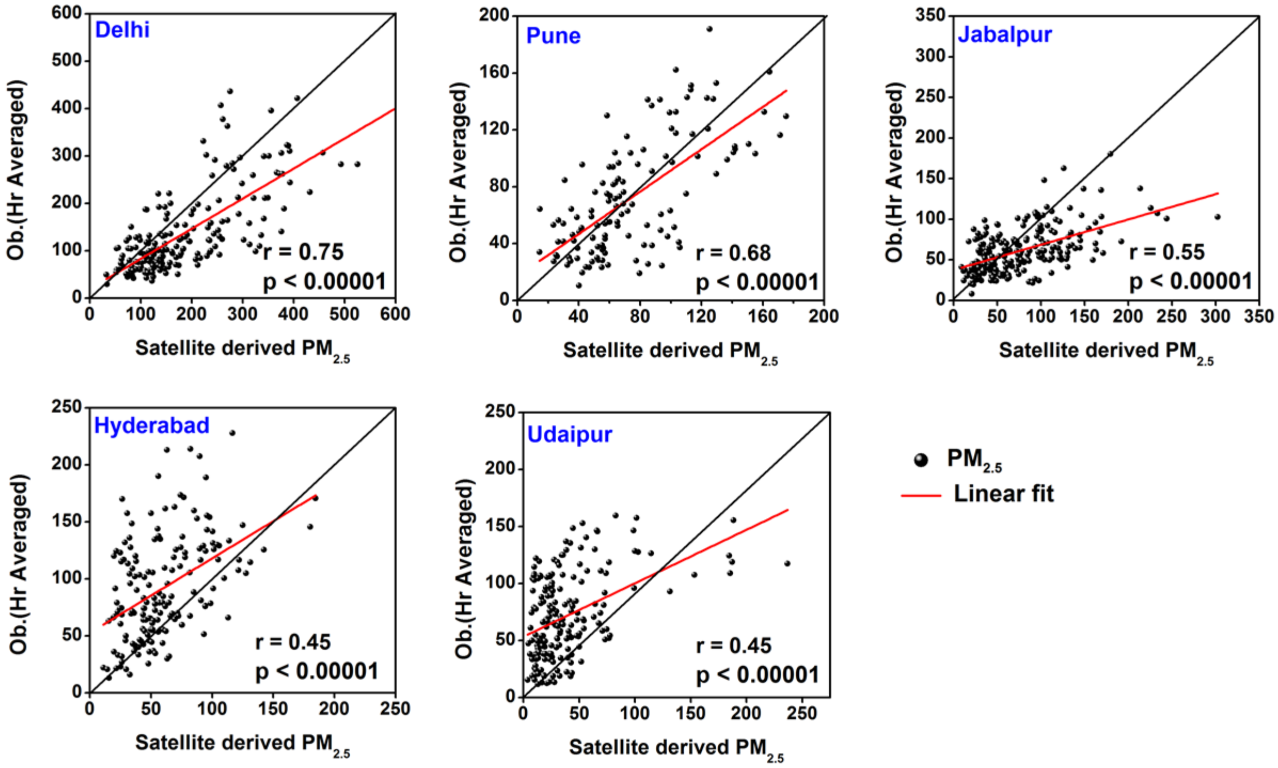

Fig. 9. Scatter plot values between observed and satellite derived $PM_{2.5}$ (in μg m^{-3}) concentrations over Delhi, Pune, Jabalpur, Hyderabad, and Udaipur.

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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