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Predicting Air Quality by Aerosol Optical Depth from MODIS

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Predicting Air Quality by Aerosol Optical Depth from MODIS

Abstract: There is an increasing interest in satellite remote sensing for estimating air quality at high spatial-temporal resolutions. This article has two fold objectives – (a) to validate aerosol optical depth (AOD_{modis}) computed using data from Moderate Resolution Imaging Spectroradiometer (MODIS) onboard Terra and Aqua satellites, and (b) to examine the association between AOD and airborne particles ≤ 10µm in aerodynamic diameter (PM_{10}). The data for this research come from four different sources – (a) AOD from NASA, (b) AOD from Aerosol Robotic Network (AERONET) at the Indian Institute of Technology (IIT) at Kanpur, (c) PM_{10} data from the Central Pollution Control Board, and (d) meteorological data from the National Climatic Data Center. Our findings suggest that the algorithm used to generate AOD using MODIS data (AOD_{MODIS}) is robust and an effective predictor of PM_{10} after controlling for meteorological conditions. The effect of seasonality becomes insignificant after accounting for the impact of dew point, which means that the empirical relationship between PM_{10} and AOD_{MODIS} observed in Kanpur can be extended to other parts of the world after controlling for local meteorological conditions.

Keywords: Aerosol optical depth (AOD), MODIS, Air Pollution, Kanpur, PM_{10}.
1. INTRODUCTION
A myriad of epidemiological studies have linked adverse health outcomes with the elevated concentration of air pollution in both developed (Cohen et al. 2005; Dockery et al. 1993; Pope and Dockery 2006; Samet and Krewski 2007) and developing countries (Pandey et al. 2003; Smith et al. 2000). While the positive association between air pollution and respiratory, cardiovascular and cardiopulmonary health outcomes is well-established, there are important data and methodological limitations that arise from uncertainty in exposure assessment (Dominici et al. 2003; Kanaroglou et al. 2005). Because air pollution data are not available at high spatial-temporal resolutions and a vast majority of studies rely on ambient air pollution recorded at a limited number of centrally located monitoring stations (Kumar and Foster 2007). Advances in satellite remote sensing and chemical transportation models (CTM) with data assimilation techniques, however, offer unique opportunity to compute indirect estimates of air quality at high spatial-temporal scales (Khattatov et al. 2000; Chai et al. 2006). CTM have been used to estimate exposure in the absence of air pollution data. But there are two major limitations in using CTM, especially for developing countries (Reddy and Venkataraman 2002). First, for developing countries CTM will have little usages because emission inventory data are rarely available, which are essential inputs for CTM. Second, the predictive power of CTM is far below the estimates from federal regulatory methods (FRM). Given these limitations, satellite remote sensing seems to be the only option to estimate air quality at high spatial-temporal resolutions.

During the past one decade, there have been significant advances in satellite remote sensing in terms of spatial-temporal coverage and resolution, for example data from MODIS onboard Terra (morning) and Aqua (afternoon) satellites have daily morning and afternoon global coverage, and provides a unique opportunity to impute global daily estimates of air quality (Chu 2006; Kumar, Chu, and Foster 2007). In principle, electromagnetic radiation $l_s$ from the earth surface changes to $l_0$ while interacting with the suspended and liquid particles present in the atmosphere prior to reaching the sensor mounted onto a satellite. In the absence of aerosols in the atmosphere $l_s \sim l_0$. Radiative transfer models have been used to compute aerosol optical depth (AOD) using the change in $l_s$ to $l_0$ (Kaufman et al. 2002; Christopher et al. 2000; Dubovik and King 2000; Remer, Tanré, and Kaufman 2006; Chu et al. 2003). AOD has three components – aerosols generated by human activities ($AOD_h$), aerosols generated by natural factors ($AOD_n$), such as change in meteorological conditions, and aerosols produced through $AOD_h \cap AOD_n$. For air quality studies, however, we are interested in $AOD_h$. While it is difficult to extract $AOD_h$ from AOD with the aid of radiative transfer models, statistical models can be employed to estimate $AOD_h$ by correcting AOD for meteorological conditions.

Although researchers have begun to explore the potential of MODIS data to estimate air quality (Chu et al. 2003; Gupta et al. 2006; Remer et al. 2005), few studies have attempted to estimate $AOD_h$ component from AOD$_{MODIS}$. The spatial-temporal variability in AOD$_{MODIS}$ can result from two main sources – meteorological conditions, such as moist air masses, and air pollution induced by human activities, contributing to $AOD_n$ and $AOD_h$, respectively. In this paper we assume that
Change in $AOD_n$ occurs more frequently by time due to change in meteorological conditions and spatial variability in $AOD_n$ is observed at a regional scale rather than at a local scale. Meteorological conditions do not show much variability within short distances, but change more frequently say within a days or weeks. In addition, meteorological conditions vary significantly across different seasons. $AOD_h$, however, records greater spatial variability but less temporal variability (Kumar, Chu, and Foster 2007), as the pattern of human induced air pollution does not change frequently, though change in meteorological conditions, such as wind direction and wind velocity can influence the patterns of local spatial variability in $AOD_h$.

Building on the above assumptions, this paper will evaluate whether air quality, measured by $AOD_h$, could be estimated from AODMODIS after accounting for the impact of meteorological conditions and seasonality. Three specific aims of this article are outlined below:

a. to evaluate the robustness of AODMODIS by examining its association with the AOD monitored at AERONET ($AOD_{AERONET}$), located in Kanpur, India.
b. to develop an empirical relationship between $AOD_{MODIS}$ and PM$_{10}$ monitored at a central location in Kanpur required to predict $AOD_h$ after controlling for meteorological conditions and seasonality, and
c. to predict indirect estimate of PM$_{10}$ at a high spatial resolution using the empirical relationship between AODMODIS and PM$_{10}$.

The remainder of this article is organized into three sections. The study area, data and methodology are described in the first section. The results are discussed in the second section. The final section includes a discussion of our findings and a summary of the results.

2. STUDY AREA, DATA AND METHODS:

2.1 Study Area: This study focuses on Kanpur, the third largest city of 2.4 million people in Indo-Gangetic plain after Delhi and Calcutta (Figure 1a and 1b) (Census of India 2001), and the only city in India where a NASA AERONET has been operational since the year 2001, and the data from AERONET were necessary to evaluate the robustness of AODMODIS. An air pollution monitoring station is also located centrally in the study area. The data from this station will allow us to develop an empirical relationship between PM$_{10}$ (ground measurement) and satellite based AODMODIS.

2.2 Data: The data for this research come from four different sources – (a) particulate matter (PM) data from the Central Pollution Control Board, Delhi, India, (b) AOD$_{MODIS}$ from NASA, (c) AOD$_{AERONET}$ from NASA, and (d) meteorological data from the National Climatic Data Center (NCDC).

2.2.1 PM Data from the Central Pollution Control Board (CPCB): Although there are several monitoring stations in Kanpur, the mass concentration of PM$_{10}$ data were
downloaded for Vikas Nagar (VN) monitoring station (CPCB 2007). Unlike other stations in the city, this station was located centrally and had the most frequent monitoring of PM$_{10}$ from 2001 to 2005. The station is located in a mixed land-use zone, partly commercial and partly residential and located within 600m of the National Highway, with a phenomenal traffic volume of all types of vehicles throughout the year. Therefore, the site represents mixed land-use and air pollution from different sources, a typical location in the central part of a city in the Gangetic plain. The central coordinates of the city are 80.29E and 26.46N.

2.2.2 Satellite Data: We used data from MODIS onboard Terra (10:30A local equatorial crossing time) and Aqua (1:30P local equatorial crossing time) satellites (NASA 2007). The National Aeronautics and Space Administration (NASA) aerosol land team wrote an algorithm to extract aerosol over land and ocean (Remer et al. 2005), and these products are made available through Goddard Earth Sciences Distribution Active Archive Center (DAAC) and from Level 1 and Atmosphere Archive and Distribution System (LAADS) in recent years (NASA 2007). These 10km (at nadir) aerosol over land and ocean product from 2000 to 2006 for MODIS Terra and 2002 to 2006 from MODIS Aqua were acquired from DAAC. The algorithm used to estimate AOD is discussed in Remer et al. (2005). The AOD products were arranged in granule and stored in HDF4 format (THG 2007). Not only does each granule covers very large geographic area (with >2000km longitudinal extent in each granule) but also includes a large number data fields organized across three groups - geolocation fields, data fields and swath attributes. Using a computer application, written in .net C++ AOD values were extracted for the geographic extent from 79.95 to 80.80E and 25.95 to 26.95N, i.e. roughly ± 0.5degree distance center on the city center of Kanpur. For particulate matter ≤10µm in aerodynamic diameter (PM$_{10}$) and AOD$_{MODIS}$ association, however, the AOD$_{MODIS}$ were restricted within 0.15degree of the monitoring station, located in the City Center, because PM$_{10}$ showed the highest intensity of relationship with the AOD$_{MODIS}$ averaged across this distance.

2.2.3 AOD$_{AERONET}$ Data: Pre- and post-calibrated AOD, recorded in different wavelengths, for Kanpur from 2001 to 2005 were downloaded from AERONET site (NASA 2007). The methodological details about these data and calibration are available elsewhere (Dubovik and King 2000; Smirnov et al. 2000; Dubovik et al. 2000). AOD$_{AERONET}$ were recorded at hourly interval, but AOD$_{MODIS}$ observation represents satellite crossing time, i.e. 10:30A for Terra and 1:30P for Aqua. Using Kumar et al.’s recommendations about spatial-temporal collocation of satellite and ground measurements (Kumar, Chu, and Foster 2007), AOD$_{AERONET}$ data were averaged within ± 90 minutes of AOD$_{MODIS}$ data, and daily AOD$_{MODIS}$ were averaged within 0.15 degree distance from the AERONET station in Kanpur, because within this distance AOD$_{MODIS}$ showed the best association with AOD$_{AERONET}$. Collocating these data by time and space resulted in daily estimates of AOD$_{MODIS}$ (for Terra and Aqua separately) and AOD$_{AERONET}$ for further analysis.

2.2.4 Meteorological Data: Hourly meteorological data for Kanpur, such as wind direction, atmospheric (sea level) pressure, visibility, temperature and dew points, from 2000 to 2006 were downloaded from the Global Surface Hourly database maintained by
the National Climatic Data Center (NCDC 2007). The meteorological data were extracted within ±90 minutes of AODMODIS (9:00-12:00h for Terra and 12:00h to 15:00h for Aqua) to integrate these data with AODMODIS as suggest by Kumar et al. (2007).

2.3 Methods: Standard descriptive and regression methods were employed. To evaluate the robustness of AODMODIS, it was regressed on AODAERONET recorded in different wavelengths. An empirical relationship between PM$_{10}$ and AODMODIS was developed after controlling for seasonality and meteorological conditions. To predict PM$_{10}$ by AODMODIS consider a simple regression model

$$(1) \quad \ln(\text{PM10}_{i,t}) = \beta_0 + \beta_1 \ln(\text{AODMODIS}_{i,t}) + \varepsilon_{it}$$

Where $i$ denotes the $i^{th}$ location centered on CPCB monitoring station and $t$ denotes time, i.e. month.

As discussed earlier AODMODIS is columnar measurement and consists of two components - $AOD_n$ and $AOD_h$. Since there is no direct mechanism to separate $AOD_n$ and $AOD_h$, introducing meteorological conditions ($W$) in the equation (1) we could account for the impact of $AOD_n$, as

$$(2) \quad \ln(\text{PM10}_{i,t}) = \beta_0 + \beta_1 \ln(\text{AODMODIS}_{i,t}) + \gamma' W' + \varepsilon_{it}$$

Where $\gamma'$ = a vector of 1 x k coefficients of meteorological conditions, and $W'$ = a matrix of $k$ meteorological conditions x $n$ (observations). Many studies have shown that meteorological conditions are autocorrelated (Chu 2006; D’Allura et al. 2006; Singh et al. 2004). Although visibility, atmospheric pressure, ceiling height and wind-velocity were correlated with the AODMODIS, dew point, an indirect measure of relative humidity, was selected to account for the impact of $AOD_n$, because not only did it register the highest correlation with other meteorological conditions but also reported the best association with AODMODIS. Temporal structure in meteorological conditions further complicates AODMODIS-PM$_{10}$ association. Therefore, controlling for temporal structure is important to predict air quality by AODMODIS. Next, consider a model that does account for both meteorological conditions and seasonality

$$(3) \quad \ln(\text{PM}_{10(s),t}) = \beta_0^s + \beta_1^s \ln(\text{AODMODIS}_{i,t}) + g(dew_{it}) + \varepsilon_{it}$$

Where the superscript $s$ denotes season and $g()$ is a simple function of dew point. This equation may be estimated using least squares applied sign seasonal-specific data. However, formally testing for differences by season is facilitated by interacting the regressors in (3) with a dummy variable $M_t$ which takes the value 1 during the monsoon and 0 otherwise as in equation 4:

$$(4) \quad \ln(\text{PM}_{10(s),t}) = \beta_0^0 + \beta_1^0 \ln(\text{AODMODIS}_{i,t}) + g_1(dew_{it}) + \alpha_0^t M_t + \alpha_1^t M_t ln(A OD_{MODIS(i,t)}) + \alpha_2^t M_t dew_{it} + M_t (g_1(dew_{it}) - g_0(dew_{it}))+ \varepsilon_{it}$$

where $\alpha_i^t = \beta_i^1 - \beta_i^0$, and testing the hypotheses that $\alpha_i^t = 0$. 

3. RESULTS:

3.1 Descriptive Statistics: Descriptive statistics of AOD\textsubscript{MODIS} and three criteria pollutants (PM\textsubscript{10}, SO\textsubscript{2} and NO\textsubscript{2}) is presented in table 1. The average concentration of PM\textsubscript{10} was recorded as 190µg/m\textsuperscript{3} in 2001-02, which increased to 198µg/m\textsuperscript{3} in 2004-05. The increase in PM\textsubscript{10} estimated using AOD\textsubscript{MODIS} was ~ 4.23 µg/m\textsuperscript{3}. These estimates are roughly four times greater than the PM\textsubscript{10} standards for the residential areas (WHO 2006; CPCB 2007). This indicates very poor state of air quality in the City. While NO\textsubscript{2} declined slightly and SO\textsubscript{2} did not change significantly, there was a significant increase in both AOD\textsubscript{MODIS} and PM\textsubscript{10} from 2001-02 to 2004-05. Unlike Delhi Kanpur did not witness any major air quality interventions in recent years. From the analysis of our data there is an indication of deterioration in air quality measured by PM\textsubscript{10} monitored on the ground, a widely accepted indicator of air quality worldwide (WHO 2000, 2006), and also by satellite based estimates of AOD\textsubscript{MODIS}.

3.2 AOD\textsubscript{MODIS} Validation: AOD\textsubscript{MODIS} from Terra and Aqua were examined with reference to AOD\textsubscript{AERONET} in different wavelengths. The results are presented in table 2a and 2b and figures 2a, 2b, 3a and 3b. There was little difference in the averages AOD\textsubscript{MODIS} (centered on AERONET station in Kanpur) from both Terra and Aqua satellites (Table 2a). The average AOD\textsubscript{AERONET} in wavelength 0.550µm (AOD\textsubscript{AERONET550}) was closer to that for AOD\textsubscript{MODIS}. The variation in AOD\textsubscript{MODIS}, however, closely coincided with that for AOD\textsubscript{AERONET} in wavelength 0.675µm (AOD\textsubscript{AERONET675}) (Figures 2b and 3b). Therefore, AOD\textsubscript{AERONET675} is a better predictor of AOD\textsubscript{MODIS} than AOD\textsubscript{AERONET550} (Table 2b) after correcting for underestimation in the intercept using the average estimates of AOD\textsubscript{AERONET550}. From the visual inspection of the scatter plots it is evident that the differences in AOD\textsubscript{MODIS} and AOD\textsubscript{AERONET} increase for high values. Therefore, excluding extreme values of AOD\textsubscript{MODIS} could avoid distortion in air quality studies. The AOD\textsubscript{AERONET675} explains about two-thirds of the total variability in AOD\textsubscript{MODIS} from Terra satellite. The value for Aqua, however, is 53%. Limited temporal coverage, sample size and higher frequency of cloud cover in the afternoon could explain this low R\textsuperscript{2} value for AOD\textsubscript{MODIS} from Aqua.

In principle, there should be one-to-one relationship between AOD\textsubscript{MODIS} and AOD\textsubscript{AERONET}. Several factors could contribute to differences between AOD\textsubscript{MODIS} and AOD\textsubscript{AERONET}. First, the spatial-temporal resolutions of these two datasets are different, for example AOD\textsubscript{MODIS} represents the AOD value at satellite crossing time, and AOD\textsubscript{AERONET} are hourly averages. Second, AOD\textsubscript{AERONET} are point measurements and AOD\textsubscript{MODIS} are areal estimate ~ 10km spatial resolution at nadir. For this analysis, we computed average of AOD\textsubscript{MODIS} within 0.15 degree distance (which showed the best association with AOD\textsubscript{AERONET}) from the AERONET station in Kanpur. Given these differences in the spatial-temporal resolutions of these two datasets, an R\textsuperscript{2} value of 64% indicates that AOD\textsubscript{MODIS} are fairly robust, and excluding extreme values could further improve this association between AOD\textsubscript{MODIS} and AOD\textsubscript{AERONET}. 
3.3 AOD\textsubscript{MODIS} - PM\textsubscript{10} Empirical Relationship: PM\textsubscript{10} observed on the earth surface is likely to show a stronger association with \textit{AOD}_h rather than with \textit{AOD}_n. Since there is no direct mechanism to separate \textit{AOD}_h from AOD\textsubscript{MODIS}, we developed an empirical relationship between PM\textsubscript{10} and AOD\textsubscript{MODIS} by sequentially controlling for the effects of meteorological conditions and seasonality as in equations 1 through 4. There were large gaps in the data, because of cloudy conditions for AOD\textsubscript{MODIS} and the failure of instrument for PM\textsubscript{10}, for example on an average PM\textsubscript{10} data were available for 188 days in a given year between 2001 to 2005, and for 171 days/year for MODIS onboard Terra from 2000-2006. Integrating these data by date will leave fewer days (~88 days/year) on which both AOD\textsubscript{MODIS} and PM\textsubscript{10} are available.

There are two potential solutions to address the gap in AOD\textsubscript{MODIS} and PM\textsubscript{10} data. First, these gaps could be filled using autoregressive model or spline functions available in standard statistical software packages, such as SAS (SAS Institute Inc. 2005). Second, data could be aggregated by higher order temporal scales, such as month. We opted for the second and restricted the analysis to monthly averages instead of filling the gap with the estimated values. The main advantage in using the aggregate estimate is that there is a significant mismatch in the temporal resolution of PM\textsubscript{10} and AOD\textsubscript{MODIS} data: PM\textsubscript{10} are the daily averages 6:00AM to 6:00AM next day and AOD\textsubscript{MODIS} represents a fraction of a minute/day when satellite is over an area. Therefore, monthly average will be more robust than the daily estimate and likely to result in one to one match for the monthly averages of PM\textsubscript{10} and AOD\textsubscript{MODIS}.

Since both AOD\textsubscript{MODIS} and PM\textsubscript{10} were skewed these were transformed to log scale. In the first model in which both datasets were pooled there was no significant relationship between ln(AOD\textsubscript{MODIS}) and ln(PM\textsubscript{10}) (table 3 and Figure 4). A scatter plot of ln(PM\textsubscript{10}) against ln(AOD\textsubscript{MODIS}) shows two different trends in the data: for monsoon and non-monsoon seasons (Figure 5). The monsoon generally reaches Kanpur towards the end of June or beginning of July and moist air mass during the monsoon season can dramatically impact the AOD value. To avoid the monsoon impact, the data were divided into two categories – monsoon (June-August) and non-monsoon periods (January-May and Sept-December). This means AOD\textsubscript{MODIS} during monsoon is very different from that in non-monsoon period, which is obvious in the second set of analyses by monsoon categories, which shows a significant positive relationship between ln(AOD\textsubscript{MODIS}) and ln(PM\textsubscript{10}). Evidently, the relationship between AOD\textsubscript{MODIS} and PM\textsubscript{10} is importantly different in the monsoon and non-monsoon periods. Indeed, the third column of results shows that, given ln(AOD\textsubscript{MODIS}), ln(PM\textsubscript{10}) is significantly lower in the monsoon period (Table 3). Because rain could wash out aerosols (and hence PM\textsubscript{10}) frequently during the monsoon season, which will result in greater variability in PM\textsubscript{10} and AOD\textsubscript{h}.

We then consider whether the introduction of a measure of relative humidity removes this monsoon effect. The fifth column incorporates the dew point and dew Point squared. As anticipated, dew point strongly predicts ln(PM\textsubscript{10}) given ln(AOD\textsubscript{MODIS}) and, after controlling for dew point, the monsoon dummy as well as interactions with the dew point are not significant. The R\textsuperscript{2} on this pooled regression is now 67%. The final column also tests for whether the relationship between ln(AOD\textsubscript{MODIS}) and ln(PM\textsubscript{10}) is different by
seasons. We find that the point estimate suggests that \( \ln(\text{AOD}_{\text{MODIS}}) \) has a weaker relationship with \( \ln(\text{PM}_{10}) \) in the *monsoon* than the non-*monsoon* period but that the difference is not significant. We may thus conclude that controlling for dew point \( \ln(\text{AOD}_{\text{MODIS}}) \) does an excellent job for predicting \( \text{PM}_{10} \) across both the *monsoon* and non-*monsoon* seasons.

### 3.5 PM\textsubscript{10} prediction with AOD\textsubscript{MODIS}:

Using the empirical relationship developed above, daily and monthly \( \text{PM}_{10} \) were predicted. The predicted \( \text{PM}_{10} \) plotted against the observed \( \text{PM}_{10} \) show a great match except for high observed values of \( \text{PM}_{10} \) (Figure 6). Given the differences in the temporal resolution of \( \text{PM}_{10} \) and AOD\textsubscript{MODIS} (Kumar, Chu, and Foster 2007), and change in boundary condition (Chu et al. 2003) these differences are reasonable. This relationship could be exploited to generate continuous air pollution surfaces, which, in turn, could be used to impute exposure at any point location with the aid of geocoding and geostatistical methods of interpolation for short- and medium-term health effects studies (Cressie 1993).

### 4. DISCUSSION:

This paper shows the robustness of satellite based AOD\textsubscript{MODIS} and its application to predict \( \text{PM}_{10} \) for a large city of a developing world. To evaluate the robustness of AOD computed using the data from MODIS onboard Terra and Aqua satellites, AOD\textsubscript{MODIS} were examined with reference to AOD monitored by AERONET in different channels in Kanpur. Tripathi et al. pursued a similar exercise for Kanpur (Tripathi et al. 2005). Their research concluded a positive association between AOD\textsubscript{MODIS} and AOD\textsubscript{AERONET}, and overestimation in AOD\textsubscript{MODIS} in pre- and during-*monsoon* seasons, which they explain by dust events in pre-*monsoon* and higher moisture contents during the monsoon season. Other studies also suggest the similar trend (Singh et al. 2004; Chinnam et al. 2006). In the present study, however, AOD\textsubscript{MODIS} recorded a stronger positive association with AOD\textsubscript{AERONET} in both channels 0.550\( \mu \)m and 0.675\( \mu \)m as compared to that reported in earlier studies.

This is the first systematic study that utilizes relatively large sample size and five years of continuous data from four different sources. AOD\textsubscript{MODIS} from Aqua and Terra satellites collocated with AOD\textsubscript{AERONET} with the optimal spatial-temporal widows of \( \pm 90 \) minutes across the satellite crossing time and 0.15 degree distance from the AERONET, respectively. Although the average of AOD\textsubscript{MODIS} was closer to that of AOD\textsubscript{AERONET}550, temporal variability in AOD\textsubscript{MODIS} matched strongly with the temporal variability in AOD\textsubscript{AERONET}675. In this study, we have validated the AOD\textsubscript{MODIS} against the ground truth, which has given us a greater confidence in utilizing AOD\textsubscript{MODIS} to construct the trends of air quality across time and space, especially for developing countries, lacking adequate spatial-temporal coverage of air pollution monitoring.

From our analysis it is clear that AOD\textsubscript{MODIS} does not adequately represent AOD\textsubscript{h}, which consists of airborne particles generated by human activities, such as fossil fuel burning. AOD\textsubscript{MODIS} consists of both AOD\textsubscript{h} and AOD\textsubscript{n}, and it is important to evaluate these two different components of AOD\textsubscript{MODIS} with reference to their sources and at different geographical scales. Since AOD\textsubscript{h} are largely from anthropogenic factors, and their
sources are local and vary greatly within short distances. $AOD_h$, however, is influenced by meteorological conditions that impact relatively larger areas. Therefore, $AOD_h$ does not vary significantly within short distances, but have regional and seasonal trends. Consequently, accounting for meteorological conditions and seasonality could control for the large scale variability in $AOD_{MODIS}$ and produce indirect estimates of $AOD_h$, required for predicting airborne particles at a greater spatial resolution. After accounting for meteorological conditions and seasonality, the $PM_{10}$ predicted by $AOD_{MODIS}$ and observed $PM_{10}$ fall along the straight line except for high $PM_{10}$ values (Figure 6). Given the differences in the temporal resolutions - 24h for $PM_{10}$ and fraction of a minute for $AOD_{MODIS}$ - these differences are not surprising, because $AOD_{MODIS}$ cannot capture afternoon dust-storm events and other events that take place in the late afternoon, evening and night.

Our analysis utilized only $AOD_{MODIS}$ from Terra for the $PM_{10}$-$AOD_{MODIS}$ association. The daily average of $AOD_{MODIS}$ from both Terra and Aqua, however, could emerge as a better predictor of $PM_{10}$ as against $AOD_{MODIS}$ separately from these two satellites, especially when hourly estimates of PM data are unavailable. The only problem in including data from both satellites was that $AOD_{MODIS}$ were not available from Aqua prior to the year 2002. Change in boundary layer height can also influence $PM_{10}$-$AOD_{MODIS}$ relationship (Chu et al. 2003). This research, however, does not account for the boundary layer height, as these data were not readily available at the required spatial-temporal resolutions of $AOD_{MODIS}$ data.

There is an increasing interest in the use of satellite data to predict airborne particles of different sizes, particularly ≤2.5µm (PM$_{2.5}$) and ≤10µm (PM$_{10}$) in aerodynamic diameters, widely accepted standard measures of air quality worldwide (WHO 2006). Although $AOD_{MODIS}$-$PM_{10}$ association has been examined for many cities across the world (Chu 2006; Chu, Kaufman, and Ichoku 2002; Li et al. 2005; Gupta et al. 2006; Kumar, Chu, and Foster 2007), $AOD_{MODIS}$-$PM_{10}$ association reported for Delhi reported in Kumar et al. (2007), however, is particularly relevant for this research, because both cities are located in the Indo-Gangetic plain and experience almost similar topographic and climatic conditions year round. The strength of $AOD_{MODIS}$-$PM_{10}$ association for Kanpur is similar to that reported for Delhi; in Delhi $AOD_{MODIS}$ predicted 85% of the total variability in $PM_{10}$ after accounting for the influence of sea level relative humidity and atmospheric pressure (Kumar, Chu, and Foster 2007).

Delhi study utilizes $AOD_{MODIS}$ at two different spatial resolutions – 5km and 10km (Kumar, Chu, and Foster 2007; Kumar, Chu, and Foster 2007). In the first, the association of $AOD_{MODIS}$ (at 5km spatial resolution) is examined with $PM_{2.5}$ and $PM_{10}$ monitored at 113 sites. The direct comparison of $AOD_{MODIS}$-$PM_{10}$ association for Kanpur with that for the first part of this study is not plausible because the time period for Delhi study was July-December 2003, and $AOD_{MODIS}$ were estimated at 5km spatial resolution. Nevertheless, contrasting our findings with that reported for Delhi suggests that $AOD_{MODIS}$ at a finer spatial resolution and $PM_{10}$ at a greater temporal scale (such as hourly) could improve the $AOD_{MODIS}$-$PM_{10}$ association; 5km $AOD_{MODIS}$ predicted 85%
of the total variability in PM$_{10}$ observed ±15 minutes of satellite crossing time after accounting for the influence of meteorological conditions.

In the second part of Delhi study, monthly 10km AOD$_{MODIS}$ centered on one monitoring station in Delhi explained 53% of the total variability in PM$_{10}$ across non-monsoon months from 2000-2005. This suggests that AOD$_{MODIS}$ could underestimate PM$_{10}$ if seasonality is not accounted for adequately. For the Kanpur analysis, however, controlling for seasonality and meteorological conditions together the AOD$_{MODIS}$ (from Terra satellite alone) predicted 67% of the total variability in PM$_{10}$ despite significant mismatches in the spatial-temporal resolutions of these two datasets. A unit of AOD in Delhi was equal 68.24µg/m$^3$ of PM$_{10}$, and the value for Kanpur was very close ~ 66.23 µg/m$^3$, indicating that the empirical AOD$_{MODIS}$-PM$_{10}$ association observed in one city can be extrapolated to other cities once AOD$_{MODIS}$ is controlled for meteorological conditions. Although the sources and compositions of aerosols vary regionally, these findings can also be extrapolated to other parts of the world, as the impact regional seasonality (i.e. monsoon) become insignificant after controlling for dew point alone. Moreover, the similar PM$_{10}$-AOD$_{MODIS}$ relationship is observed in other parts of the world, for example, 1AOD in Po Valley in Italy was ~ 62 µg/m$^3$ (Chu et al. 2003), which is close the value observed for Delhi and Kanpur. This means controlling for meteorological conditions one could estimate AOD$_h$ with the aid of AOD$_{MODIS}$ worldwide.

This article demonstrates the usage of AOD$_{MODIS}$ to predict PM$_{10}$, which are critically important for air quality surveillance and management in developing countries, lacking air pollution monitoring needed to generate estimates of air quality at high spatial-temporal resolutions. However, we should not overlook at the inherent problems with AOD$_{MODIS}$ data. First, AOD cannot be estimated for the areas covered by clouds on a given day. Second, uncertainty in AOD can vary for different land-use types, for example over vegetated areas it is relatively small as compared that for built-up areas (Chu et al. 2003). Finally, the spatial resolution of AOD$_{MODIS}$ product is 10km. Other studies suggest that improving spatial resolution could improve the PM-AOD$_{MODIS}$ association (Li et al. 2005; Kumar, Chu, and Foster 2007). The future research should be geared towards three main areas – minimizing uncertainty in AOD$_{MODIS}$ retrieval, improving spatial resolution of these AOD$_{MODIS}$ product and exploring statistical methods for imputing the missing value due to cloud cover. Addressing these problems will be valuable in adopting AOD as a standard measure of air quality instead of predicting PM$_{10}$ or PM$_{2.5}$ by it. It will have two major advantages. First, it will avoid errors and uncertainty in developing an empirical relationship between PM-AOD$_{MODIS}$. Second, the use of AOD$_{MODIS}$ alone could approximate both air quality and meteorological conditions, which have been used as confounding factors in time-series analysis of mortality (Health Effects Institute 2003; Bell, Samet, and Dominici 2004). Therefore, daily satellite based AOD, two times a day, with the global coverage offers a unique opportunity to estimate air quality at unprecedented spatial-temporal resolutions for air quality management and health effect research. The other unique thing that emerge from this research is that after controlling for dew point alone the effect of monsoon, which is a region specific season, became
insignificant, which means controlling for dew point alone could be used to predict air
quality worldwide with the aid AOD_{MODIS}.

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dioxide and sulfur dioxide - Global update 2005 - Summary of risk assessment*
Table 1: AOD and major pollutants – a descriptive statistics, 2001-2005 (μ ± 95% CI)

<table>
<thead>
<tr>
<th>Year</th>
<th>AOD</th>
<th>PM₁₀</th>
<th>SO₂</th>
<th>NO₂</th>
</tr>
</thead>
<tbody>
<tr>
<td>2001-02</td>
<td>0.660±0.099</td>
<td>190.55±41.53</td>
<td>4.19±0.24</td>
<td>22.96±3.77</td>
</tr>
<tr>
<td>2004-05</td>
<td>0.743±0.104</td>
<td>198.31±39.33</td>
<td>4.11±0.10</td>
<td>19.99±2.30</td>
</tr>
<tr>
<td>2004-05 to 2001-02</td>
<td>0.083</td>
<td>7.77</td>
<td>-0.08</td>
<td>-2.96</td>
</tr>
<tr>
<td>Total</td>
<td>0.706±0.073</td>
<td>194.62±28.23</td>
<td>4.15±0.12</td>
<td>21.40±2.18</td>
</tr>
</tbody>
</table>

Table 2a: Robustness of AODmodis – association between AOD_modis and AOD_aeronet

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>µ±95% CI</td>
<td>Observations</td>
</tr>
<tr>
<td>AOD_modis</td>
<td>0.627±0.026</td>
<td>601</td>
</tr>
<tr>
<td>AOD_aeronet550</td>
<td>0.559±0.020</td>
<td>607</td>
</tr>
<tr>
<td>AOD_aeronet675</td>
<td>0.457±0.018</td>
<td>607</td>
</tr>
</tbody>
</table>

Table 2b: Robustness of AOD_modis – association between AOD_modis and AOD_aeronet

<table>
<thead>
<tr>
<th></th>
<th>Terra</th>
<th>Aqua</th>
</tr>
</thead>
<tbody>
<tr>
<td>ln(AOD_aeronet550)</td>
<td>0.805</td>
<td>0.875</td>
</tr>
<tr>
<td>ln(AOD_aeronet675)</td>
<td>(28.79)**</td>
<td>(32.56)**</td>
</tr>
<tr>
<td>Constant</td>
<td>-0.234</td>
<td>-0.408</td>
</tr>
<tr>
<td></td>
<td>(11.78)**</td>
<td>(21.39)**</td>
</tr>
<tr>
<td>Observations</td>
<td>601</td>
<td>601</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.58</td>
<td>0.64</td>
</tr>
</tbody>
</table>

Absolute value of t statistics in parentheses
* significant at 5%; ** significant at 1%
Table 3: Empirical relationship between AOD\textsubscript{modisTerra} and PM\textsubscript{10}.

<table>
<thead>
<tr>
<th>ln(PM10)</th>
<th>Both Seasons</th>
<th>Monsoon Seasons</th>
<th>For non-Monsoon</th>
<th>Both seasons, Monsoon dummy</th>
<th>Aggregate model with ln(PM10)</th>
</tr>
</thead>
<tbody>
<tr>
<td>ln(AOD)</td>
<td>0.05</td>
<td>0.811</td>
<td>1.138</td>
<td>0.969</td>
<td>0.674</td>
</tr>
<tr>
<td></td>
<td>(0.2)</td>
<td>(3.08)**</td>
<td>(2.17)</td>
<td>(3.76)**</td>
<td>(2.91)**</td>
</tr>
<tr>
<td>Dew Point (C)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>0.154</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>(2.15)*</td>
</tr>
<tr>
<td>Dew Point^2</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>-0.006</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>(2.42)*</td>
</tr>
<tr>
<td>Monsoon Category</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>-0.957</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>(5.31)**</td>
</tr>
<tr>
<td>Dew Point * Monsoon Category</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>-0.002</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>(0.05)</td>
</tr>
<tr>
<td>ln(AOT)*Mons oon Category</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>-0.351</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>(0.76)</td>
</tr>
<tr>
<td>Constant</td>
<td>5.175</td>
<td>5.783</td>
<td>4.931</td>
<td>5.872</td>
<td>4.86</td>
</tr>
<tr>
<td></td>
<td>(39.85)**</td>
<td>(36.41)**</td>
<td>(30.55)**</td>
<td>(35.65)**</td>
<td>(9.42)**</td>
</tr>
<tr>
<td>Observations</td>
<td>41</td>
<td>27</td>
<td>14</td>
<td>41</td>
<td>40</td>
</tr>
<tr>
<td>R-squared</td>
<td>0</td>
<td>0.28</td>
<td>0.28</td>
<td>0.43</td>
<td>0.67</td>
</tr>
</tbody>
</table>
Figure 1a: Delhi, Kanpur and other major cities in North India.
Figure 1b: The location of Kanpur and adjacent places along with major road and rail network.
Figure 2a: Association between AOD\textsubscript{aeronet550} and AOD\textsubscript{modisTerra}
Figure 2b: Association between AOD$_{aeronet675}$ and AOD$_{modisTerra}$, 2001-2005.
Figure 3a: Association between AOD_{aeronet550} and AOD_{modisAqua}, 2001-2005
Figure 3b: Association between AOD_{aeronet675} and AOD_{modisAqua}
Figure 4: AOD from MODIS (onboard Terra) and PM$_{10}$. 
Figure 5: Monthly AOD from MODIS (onboard Terra) and $\text{PM}_{10}$ for monsoon and non-monsoon seasons.
Figure 6: PM$_{10}$ predicted using AODmodis and PM$_{10}$ observed at Vikas Nagar monitoring station.