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An empirical relationship between PM_{2.5} and aerosol optical depth in Delhi Metropolitan

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Abstract

Atmospheric remote sensing offers a unique opportunity to compute indirect estimates of air quality, which are critically important for the management and surveillance of air quality in megacities of developing countries, particularly in India and China, which have experienced elevated concentration of air pollution but lack adequate spatial–temporal coverage of air pollution monitoring. This article examines the relationship between aerosol optical depth (AOD) estimated from satellite data at 5 km spatial resolution and the mass of fine particles $\leq 2.5 \mu\text{m}$ in aerodynamic diameter (PM_{2.5}) monitored on the ground in Delhi Metropolitan where a series of environmental laws have been instituted in recent years.

PM_{2.5} monitored at 113 sites were collocated by time and space with the AOD computed using the data from Moderate Resolution Imaging Spectroradiometer (MODIS onboard the Terra satellite). MODIS data were acquired from NASA's Goddard Space Flight Center Earth Sciences Distributed Active Archive Center (DAAC). Our analysis shows a significant positive association between AOD and PM_{2.5}. After controlling for weather conditions, a 1% change in AOD explains $0.52 \pm 0.202\%$ and $0.39 \pm 0.15\%$ change in PM_{2.5} monitored within ± 45 and 150 min intervals of AOD data. This relationship will be used to estimate air quality surface for previous years, which will allow us to examine the time–space dynamics of air pollution in Delhi following recent air quality regulations, and to assess exposure to air pollution before and after the regulations and its impact on health.

Keywords

PM_{2.5}; Aerosol optical depth (AOD); Air pollution; Remote sensing

1. Introduction

Elevated concentration of air pollution and its associated health effects in rapidly growing megacities of developing countries particularly that of India and China have drawn our attention in recent years. Therefore, it is critically important to monitor air quality at high spatial–temporal resolutions. But limited network of air pollution monitoring in developing countries restricts our ability to evaluate time–space dynamics of air pollution and its effect

on human health. Nonetheless, advances in satellite remote sensing seem promising to compute indirect estimates of particle smaller than ≤ 2.5 and ≤ 10 μm in aerodynamic diameters ($\text{PM}_{2.5}$ and PM_{10} , respectively) over a large area frequently and inexpensively (Chu et al., 2003). Satellite imageries record electromagnetic radiation from the earth surface. When the radiation travels through the atmosphere, it interacts with aerosols—fine solid and/or liquid particles suspended in the air—prior to reaching the sensor mounted onto satellites. The distortion caused by this interaction can be estimated with the aid of radiative transfer model and converted into aerosol loading, also known as aerosol optical depth (AOD), which has shown a strong positive relationship with the $\text{PM}_{2.5}$ and PM_{10} observed on the surface (Chu et al., 2002, 2005; Gupta et al., 2006).

Building on these innovative methods, this article has two main goals: (a) to establish an empirical relationship between satellite-based AOD, an indirect measure of air quality, and particulate matter (PM) monitored on the earth surface in Delhi Metropolitan and (b) to examine whether AOD can effectively predict $\text{PM}_{2.5}$ and PM_{10} surfaces at high spatial-temporal resolutions. There are various measures of air quality. However, suspended particles, especially $\text{PM}_{2.5}$ and PM_{10} , have been a widely accepted measure of air quality (WHO, 2000). Therefore, the term *air quality* will refer to as the ambient concentration of $\text{PM}_{2.5}/\text{PM}_{10}$ in the remaining parts of this paper.

The need for this work emerged from our desire to model the effects of improvement in air quality on respiratory health in response to a series of recently instituted air quality regulations in Delhi, the capital of India and the only city that was subject to these regulations (Fig. 1a). Due to limited spatial-temporal coverage of air pollution data in Delhi, we began to explore the potential of satellite remote sensing to study the effect of these regulations on the time-space dynamics of air pollution, and the present article is an outcome of these explorations. This paper examines the relationship between AOD and $\text{PM}_{2.5}$ in Delhi Metropolitan, and this relationship will formulate the basis to assess change in air quality and the burden of mortality and morbidity alleviated in response to these regulations. The next three sections present the data and methods, results and discussion.

2. Data and methods

2.1. Data

The data for this research come from four different sources: (a) air quality monitoring in Delhi and its surroundings, (b) Terra MODIS (Moderate Resolution Imaging Spectroradiometer), (c) the Indian Meteorological Department and (d) the National Climatic Data Center.

2.1.1. Air pollution data—Air pollution data on suspended particulates were collected at 113 sites in the study area from July 23 to December 3, 2003 (Fig. 1b). Since our major focus was on estimating spatial variability in air pollution, a spatially dispersed sampling design was adopted (Kumar, 2007). Sample sites were identified using a two-step process—first, a rectangular grid was overlaid onto the study area, which ensured coverage of the entire study area, and second, a random location was simulated within each cell (of the size $1 \times 1.5 \text{ km}^2$) to avoid bias in the site selection. The simulated locations were then transferred to a Garmin Global Positioning System (GPS) to navigate them and examine their suitability. Some sites, which were inaccessible, were re-simulated, and finally 113 sites were found to be suitable. At each site, air was sampled at two different times every third day. Although air was sampled at different times between 7:30 a.m. and 10:00 p.m. from July to December 2003, data for the present analysis were extracted using three conditions: (a) ± 150 min of satellite crossing time, generally 10:30 a.m. local time, to minimize the effect of temporal noise in the ground measurements of PM; (b) for the months of October

and November 2003 to minimize the effect of weather conditions on AOD, because AOD is very sensitive to weather conditions and only these months in Delhi observe relatively stable weather conditions; and (c) relative humidity $\leq 50\%$.

The Aerocet 531, a real-time photometric sampler (Met One Inc, 2003), was used to collect air pollution data. It is an automatic instrument that estimates PM in a range of 1, 2, 5, 7 and 10 μm in aerodynamic diameters in mass mode, and $\text{PM}_{\leq 0.5}$ and $\text{PM}_{\leq 10}$ in count mode. The instrument uses a right angle scattering method at 0.780 μm . The source light travels at a right angle to the collection system and detector, and the instrument uses the information from the scattered particles to calculate a mass per unit volume. A mean particle diameter is calculated for each of the five different sizes. This mean particle diameter is used to calculate a volume (cubic meters), which is then multiplied by the number of particles and then a generic density ($\mu\text{g m}^{-3}$) that is a conglomeration of typical aerosols. The resulting mass is divided by the volume of air sampled for mass per unit volume measurement ($\mu\text{g m}^{-3}$). Each sample (in mass) mode takes 2 min. Particle mass estimation using this technology can be influenced by increase in relative humidity (McMurry et al., 1996). However, this problem can be addressed by excluding observation with high relative humidity ($\geq 50\%$) because the particle size and its mass inflates dramatically when relative humidity is greater than 50%, or by calibrating data with the aid of an empirical relationship between the distortion in PM mass and relative humidity developed by Lowenthal et al. (1995).

One sample site was established beside air pollution monitoring station run by the Central Pollution Control Board (CPCB). This station is equipped with gravimetric samplers and records PM_{10} and TSP regularly using high-volume samplers. At this site, we monitored PM_{10} and $\text{PM}_{2.5}$ from July to November 2003, though $\text{PM}_{2.5}$ data were not recorded at the CPCB facility. Unlike TEOM series 1400a, which measures $\text{PM}_{2.5}$ mass in real time, no instrument was installed in Delhi and its environs for comparison purposes (Thermo Electron Corporation, 2006). Thus, the only choice left was to compare photometric estimate of PM_{10} mass from Aerocet 531 with the PM_{10} mass from gravimetric measurements by high-volume sampler (Fig. 2). The average PM_{10} mass by Aerocet 531 was $157 \pm 24 \mu\text{g m}^{-3}$ during July–November 2003 which was significantly lower than PM_{10} mass from gravimetric sampler $210 \pm 18.6 \mu\text{g m}^{-3}$. Given the differences in the method and duration of the sampling between gravimetric and real-time photometric samplers, the average difference ($\leq 54 \mu\text{g m}^{-3}$) seems reasonable, because the Aerocet 531 estimates are based on 8 min of sampling—4 min each during peak and off peak hours every third day. Gravimetric measurements, however, were based on 8 h of sampling across three shifts in a day. In the absence of gravimetric measurements of $\text{PM}_{2.5}$, it was not possible to validate $\text{PM}_{2.5}$ with the gravimetric measurements. Nonetheless, our recent experiment in Delhi from September to November 2006 shows that the difference between gravimetric and photometric estimates of $\text{PM}_{2.5}$ mass is significantly smaller than that of PM_{10} .

Weather conditions, particularly relative humidity, can greatly affect mass of aerosol from photometric technology, because the concentration measurement of light-scattering devices increases with the increase in average particle size under the influence of humidity (McMurry et al., 1996). Ramachandran et al. (2003) have exploited the relative humidity correction curve developed by Lowenthal et al. (1995) to compute robust estimate of gravimetric standard $\text{PM}_{2.5}$ mass from photometric samplers. Their analysis shows that the error increases from 6% at 40% relative humidity to 40% at 70% relative humidity. Thus, the bias of relative humidity was controlled by restricting the data to the less than 50% relative humidity and by introducing relative humidity as one of the confounders in the regression model.

2.1.2. Satellite data—Data from MODIS (onboard Terra satellite) were acquired from NASA's Goddard Earth Sciences Distributed Active Archive Center (DAAC). Although air pollution data were recorded from July to December, satellite data were acquired for the months of October and November 2003 because of stable weather conditions during these 2 months. During this 2-month period, AOD values were retrieved at 5 km spatial resolution from cloud-free images, and the 10 km AOD for the same period were downloaded from DAAC.

2.1.3. Meteorological data—We used a probe with the Aerocet 531 instrument to record temperature and relative humidity in real time. Other meteorological data on sea-level atmospheric pressure, wind velocity, wind direction and rainfall were acquired from the Indian Meteorological Department at 3-h intervals, and daily meteorological data were downloaded from the National Climatic Data Center.

2.1.4. Data integration—PM data, collected at 113 sites, were point data, and AOD MODIS data were at 5 and 10 km pixel sizes (at nadir), which created the problem of geographic misalignment. For example, on a given day, two or more sample sites could be located in the same 5 km AOD pixel. Thus, data were integrated using one-to-many (same AOD value for all points within a pixel (Fig. 3)) and many-to-one (average value of PM at many sample sites to the AOD pixel) relationships. Assigning one AOD value to all sample sites within the pixel allowed us to model PM_{2.5} as a function of AOD at point level, which is referred to as the disaggregate/point-level analysis in the subsequent sections. Although the intra-AOD pixel noise in PM_{2.5} was evident from the preliminary analysis, the disaggregate analysis allowed us to assess the association between AOD and PM_{2.5} without losing the spatial resolution of point data. In the aggregate analysis, however, we averaged point measurements of PM_{2.5} data to match the spatial resolution of AOD data. This will be referred to as aggregate/pixel-level analysis in the subsequent sections.

2.2. Methods

Aerosols are solid and liquid particles suspended in the air, and AOD can be defined as will be the extinction of beam power due to the presence of aerosols in the atmosphere. AOD typically decreases with increasing wavelength for fine-mode dominated aerosols. Visible spectral bands of various remote sensing satellites have been used to estimate AOD over both water and land surfaces (Christopher et al., 2000; Chu et al., 2003, 2005; Holben et al., 1992; King et al., 1999; Wang and Christopher, 2003). In essence, AOD (τ) at a given site s is the log of the ratio of irradiance at the top of atmosphere (I_0) to irradiance at the surface (I_s). Scattering due to the presence of aerosol increases and decreases the beam power towards and against the direction of sensor Ω , respectively. The effect of aerosols loading (due to scattering and/or absorption) on radiances recorded by the sensor is computed using a radiative transfer model (Kaufman et al., 1997; King et al., 1999).

Aerosol retrieval over land is more complicated than over sea, because the land surface shows large variability, from dark vegetation to bright desert and snow/ice-covered regions. Owing to the competing processes of surface reflection and aerosol backscattering in radiative transfer, radiance measured with less surface interference results in a smaller uncertainty in the retrieved aerosol properties. The dark target approach is based on the correlation between the chlorophyll absorption of vegetation in the visible (0.47 and 0.66 μm) and liquid water absorption at 2.1 μm (reflectance <0.25). The fine-mode particles (urban/industrial and biomass-burning aerosols) are transparent at 2.1 μm (i.e., minimal aerosol effect), which allows direct observation of the earth's surface, even through heavy pollution, to estimate the surface reflectance in the visible spectrum. The MODIS AOD is computed at 0.47 and 0.66 μm by matching the averaged reflectance (after screening for

clouds, water and snow/ice pixels from a total of 100 pixels) at a $5 \times 5 \text{ km}^2$ grid to the value of a pre-calculated lookup table under the same Sun–satellite geometrical condition. The selection of $5 \times 5 \text{ km}^2$ is mainly due to large surface variability of concern at a global scale. It can be enhanced to meet different requirements of applications (e.g., urban air quality) under proper conditions. In general, the errors are within $\Delta\tau_a = \pm 0.05$ and $\Delta\tau_a = \pm 0.20\tau_a$ over vegetated and semi-vegetated regions, respectively (Chu et al., 2002).

The lookup table is constructed by Dave's code (Dave and Gazdag, 1970), which assumes spherical particle shape, an “average” aerosol profile, and lognormal size distributions (Chu et al., 2003). Three general aerosol types have been considered: urban/industrial pollution, biomass-burning aerosols, and dust. The spectral aerosol path radiance is used to separate dust from the other two types, because dust particles are significantly larger than pollution or smoke particles. Mixture of dust and non-dust aerosols is taken into account by the fine-mode fraction obtained from the linear interpolation from the derived path radiance ratio and the assumed ratio of dust and pollution (or smoke) models. Since pollution and biomass-burning aerosols both are dominated by fine-mode particles, they are distinguished by a priori assumptions based on geography varying with season. Using this methodology, AOD values were computed for 40 days, and PM and AOD data were integrated for the matching days.

The link between AOD and $\text{PM}_{2.5}$ observed at the surface is through the integration of layers of particles from the surface to the top of the atmosphere (more precisely the top of the tropopause if no stratospheric aerosols exist, or the top of the boundary layer if all particles reside within boundary layer). Good correlations between AOD and $\text{PM}_{2.5}$ are generally found if particles are within the boundary layer (since they are well mixed). Aloft particles that are present in the atmosphere, such as smoke or dust from long-range transport, result in no (or poor) correlation with surface-measured PM.

Regression models were employed to examine the association between AOD estimates from satellite data and PM mass observed on the ground. We examined this association at two different geographic scales—at point level and 5 and 10 km AOD pixel levels. In the latter, also referred to as aggregate analysis, the average $\text{PM}_{2.5}$ within 5 and 10 km AOD pixel (j) was modeled as a function of AOD at j th pixel and weather conditions as in Eq. (1):

$$\text{PM}_j = \alpha + \beta\tau_j + \lambda w'_j + \phi\sigma_{\text{PM}_j}^2 + \varepsilon_{ij}, \quad (1)$$

where PM_j is the average PM (either $\text{PM}_{2.5}$ or PM_{10}) for j th pixel; τ_j the AOD value estimated from MODIS data at j th location; w'_j the matrix of confounders, including relative humidity and temperature; $\sigma_{\text{PM}_j}^2$ the intra-pixel variance in PM, also referred to as intra-pixel noise; and ε_j the unobserved random error.

In the disaggregated analysis, PM at i th sample site located in j th pixel was modeled as a function of AOD (τ) for the pixel in which i th sample site is located and confounders (as in Eq. (2)). Since all sample sites (in a given day) within a pixel were assigned the same AOD value, resulting in an intra-pixel correlation structure in AOD, the pixel-level random effect was introduced to compute pixel-independent estimates, as in Eq. (2):

$$\text{PM}_{2.5ij} = \alpha + \beta\tau_j + \lambda w_{ij} + (\delta_j + \varepsilon_{ij}), \quad (2)$$

where δ_j is the pixel-level random effect.

Direct evaluation of the predictive power of the model is complicated by the fact that the PM measures are effectively sampled at a different resolution than the AOD measures. In particular, one would like to know the predictive value of AOD in terms of average true PM at the level of an AOD pixel. The problem is that we only have a small sample of the PM measures at the pixel level, and thus the R -squared from Eq. (2) will underestimate the percentage of variation that could be explained for average PM (averaged across all possible locations in a given AOD pixel). Nonetheless, this estimate can be constructed from the estimated random-effect errors:

$$R^2_{\text{Pixel}} = \frac{1 - \text{Var}(\delta_{ij})}{\text{Var}(\text{PM}_{ij}) - \text{Var}(\varepsilon_{ij})}. \quad (3)$$

3. Results

PM_{2.5} and AOD surfaces were generated using the data averaged for the months of October and November 2003 (Fig. 4). There are some similarities in PM_{2.5} and AOD surfaces and both observed high values in the areas near industrial clusters. The summary statistics of PM and AOD are reported in Table 1. While the concentration of PM varies greatly in Delhi, the AOD concentration varies significantly outside Delhi, albeit the AOD variance is much smaller than the variance of PM (Table 1), which is expected given the coarser spatial resolution (5 km) of AOD and PM data at the point location. The average concentrations of PM_{2.5} and PM₁₀ between August and November 2003 in Delhi were recorded as $82.9 \pm 7.8 \mu\text{g m}^{-3}$ (at 95% confidence interval) and $304.2 \pm 29.8 \mu\text{g m}^{-3}$, respectively, which are significantly higher than the US EPA standards. The average AOD measurements in Delhi during the months of October and November 2003 were estimated as 0.64 ± 0.023 and 0.65 ± 0.025 at 5 and 10 km spatial resolutions, respectively. The average AOD values were also computed with reference to distance from the city's center (Connaught Place). Table 2 shows a gradual decline in the average AOD with increasing distance from the city's center; the AOD concentration drops from 0.664 within 0.1 decimal degree (about 9.17 km) to 0.545 within 0.5 decimal degree (about 48.5 km) distance from the city's center. The gradient of decline in AOD is higher at 5 km spatial resolution than that at 10 km resolution.

The scatter plots at both point (disaggregated) and pixel (aggregated) levels reveal a positive association between PM_{2.5} and AOD (Fig. 5a and b). From Fig. 5a it is evident PM_{2.5} varies significantly within a 5 km pixel, and hence the point-level estimates of PM_{2.5} are noisy for 5 km AOD pixel. Two different approaches were adopted to address this problem—first, R^2 values for intra-pixel noise in PM_{2.5} were adjusted using Eq. (3), and second, point-level estimates of PM_{2.5} were aggregated to pixel level. Although the average PM_{2.5} plotted against AOD shows improvement in the PM_{2.5}–AOD association, the points still deviate significantly from the line of best fit (Fig. 5b), which means that there are factors (including weather conditions) other than AOD that influence PM_{2.5}.

In the preliminary analysis, PM_{2.5} was regressed on AOD at both 5 and 10 km spatial resolutions. Given the substantial intra-pixel variability, the AOD did not emerge as an effective predictor of PM_{2.5} at 10 km spatial resolution. Thus, the final analysis was restricted to 5 km AOD only. The regression results of point- and pixel-level analyses are presented in Tables 3 and 4, respectively. The AOD was computed using the data from MODIS onboard Terra satellite, which records electromagnetic energy just once in a day in the morning, generally 10:30 a.m. local time. Thus, the AOD estimates are the true representatives of aerosol loading at the time electromagnetic energy was recorded. PM_{2.5} measurements on the ground (even with 2 min of sampling window), however, will not match the satellite overpass time very precisely. Therefore, the uncertainty in AOD–PM_{2.5}

association is likely to increase as the time of PM_{2.5} observation deviates from the overpass time of satellites. To examine this effect, the analysis was conducted separately at 15 min time intervals within ± 150 min of the overpass time of the Terra satellite.

As mentioned above, weather conditions can greatly influence aerosol loading. Thus the effect of weather conditions, such as wind velocity, relative humidity, temperature and atmospheric pressure, can confound the AOD–PM_{2.5} association. Among these, relative humidity and sea-level atmospheric pressure, which also experienced significant association with the wind direction, were used in the final analysis. Both relative humidity and sea-level atmospheric pressure showed a statistically significant impact on PM_{2.5}.

The 5 km AOD shows a statistically significant positive association with PM_{2.5} in both disaggregate (Table 3) and aggregate (Table 4) analyses. At the point level, 1% change in AOD explains 0.398% (± 0.151 at 95% confidence level) change in PM_{2.5} ± 150 min of AOD data (i.e., the overpass time of EOS Terra satellite). The predictive power of AOD is stronger for shorter time intervals; for example, within a 45 min time interval, a 1% change in AOD (holding other variables constant) explains 0.52% and 0.45% change in PM_{2.5} at point and pixel levels, respectively. In the study area, the concentration of PM varies significantly. Consequently, the daily estimate of PM for a given pixel is expected to be noisy. But after controlling for this noise, the R^2 value increases substantially; for example, within a ± 15 min interval, the R^2 values increased to 76% and 81% for PM_{2.5} at point and pixel levels, respectively (Tables 3 and 4).

Fig. 4 shows the average estimates of AOD and PM_{2.5} during the months of October–November 2003. There are some similarities in the spatial distributions of PM and AOD. One of the important findings that emerges from this figure is that the areas in and around industrial clusters show elevated concentrations of both PM and AOD, except in the southwestern parts. The average AOD gradually declines with increasing distance from the city's center. The average concentration of AOD (τ) in the northeastern parts of Delhi was more than 0.6, and the figures outside Delhi boundaries are less than 0.5. The spatial variability in AOD does not perfectly matches with that of PM_{2.5} because of several reasons: (a) the spatial–temporal resolutions of AOD–PM_{2.5} data do not match perfectly—AOD were estimated at about 10:30 a.m. and their spatial resolution was 5 km; PM data, however, were spread ± 150 min of AOD data and these data were recorded at 113 point locations; (b) AOD are column measurements and PM_{2.5} were recorded at 5 feet above the surface; (c) unlike daily match of AOD–PM_{2.5} for regression analysis, maps of AOD and PM_{2.5} are based on the averages for the entire 2 months; and (d) PM_{2.5} surface was interpolated using Kriging methods, while AOD surface is true to its spatial resolution and did not require any interpolation.

4. Discussion

As far as the association between the 5 km AOD and PM concentration is concerned, our results are consistent with the findings of the existing literature (Chu et al., 2003; Gupta et al., 2006). The AOD, in association with relative humidity and sea-level atmospheric pressure, explains more than 70% variability in PM_{2.5} within ± 150 min of overpass time window of the ESO Terra satellite and these estimates account for intra-pixel noise in PM. The PM–AOD association in Delhi is weaker than that reported in other parts of the world (Chu et al., 2005). As described above, the concentration of PM varies significantly across space and time. Therefore, it is critically important to match the spatial–temporal resolutions of AOD and PM as closely as possible. Although the 5 km AOD data used in the analysis is the first ever attempt to compute AOD from MODIS data at such a fine spatial resolution and collocated with a large number of spatially dispersed sites in the study area, we have

observed substantial variability in PM_{2.5} within 5 km pixel. Moreover, for research on health effects we will need geographically detailed information on air pollution to compute precise exposure to ambient air pollution. Our future research aims at improving algorithms for computing AOD at 2.5 and 1 km spatial resolutions.

The temporal variability can be addressed by collecting air pollution data at different time intervals. Our analysis reveals the best association between AOD and PM_{2.5} within ± 45 min of the overpass window of the EOS Terra satellite, and ± 75 min window for the association between AOD and PM₁₀. These findings have important implications for research that examines the relationship between AOD and PM in different parts of the world and for air pollution monitoring strategies.

In the absence of air pollution data at high spatial–temporal resolutions, researchers have begun to explore the potential of AOD to predict air quality in megacities in developing countries. Given the regional variations in the nature and sources of aerosol, the association between PM and AOD can vary regionally as reported by Gupta et al. (2006). This will require a field experiment to collect air pollution data using real-time samplers, because the existing air pollution monitoring stations use gravimetric method, which requires a minimum of eight or more hours of sampling, and the PM concentration reported from these samplers is the average for this duration, which can be quite noisy for PM–AOD analysis. The use of photometric samplers is one of the potential solutions for real-time monitoring of PM, and based on the results of our analysis, we recommend monitoring PM data at sufficiently large number of sites within ± 75 min of the overpass time of satellites (generally 10:30 a.m. local time). For AOD data from both Terra (morning) and Aqua (afternoon) satellites, 9:00 a.m.–3:00 p.m. will be an ideal time window for collecting PM data on the ground.

A host of factors, such as sources of air pollution, proximity to water bodies, vegetation, seasonality and weather conditions, all of which vary regionally, can influence aerosol loading and hence its relationship with PM. Future research should also aim at studying the AOD–PM association with reference to sources of air pollution, land-use type and aerosol characterization. This article demonstrates a visual association between sources of air pollution—namely industrial locations and main roads—and the concentration of AOD and PM. Another interesting finding of our research is the diminishing level of AOD with the increasing distance from the city's center, which clearly shows that air pollution distribution in the study area is an inverse function of distance from the city's center.

A myriad of studies have shown relationship between AOD from satellite data and ground measurements of PM (Chu et al., 2005; Kaufman et al., 2002; Li et al., 2005; Wang and Christopher, 2003). Satellites with MODIS have been in orbit since the year 2000 and the spatial–temporal trends of PM_{2.5} and PM₁₀ can be imputed with the aid of AOD since the 2000. But the relationship between AOD and PM observed in one region cannot be extrapolated to other, because the type and sources of aerosols and air pollution vary regionally and hence the strength of the relationship between AOD and PM. Therefore, it is important to establish an empirical relationship between AOD and PM using the current data, and use this relationship to impute estimates for the back years. It will require a field campaign to monitor PM daily at sufficiently large number of sites for about a year and then collocate PM data with the AOD data at as fine spatial–temporal resolutions as possible. Real-time photometric samplers, as demonstrated in this article, can be deployed to collect PM data at a large number of sites frequently and inexpensively.

The methodology demonstrated in this article has important implications for air quality management in the megacities of developing countries, particularly in India and China,

because these cities have experienced significant deterioration in air quality by increase in income through foreign direct investment, urbanization, industrialization and abated increase in the demand for automobiles (Bell et al., 2004; Mukherji, 2006). Although data from various satellites can be used to compute air quality estimates, data from MODIS onboard Terra and Aqua, which have a daily repetitive global coverage, are particularly useful to compute daily estimates of air pollution needed to study the health effects of the short-term exposure to ambient air pollution. The results reported in this research can be used to predict PM surfaces for previous years in the study area. Although 5 km spatial resolution is inadequate to compute exposure to ambient air pollution, it can certainly be valuable to examine the time–space dynamics of air pollution in response to recently enacted environmental laws in Delhi. Future research to compute PM surfaces from AOD at high spatial resolution is likely to pave the way to compute exposure to ambient air pollution for health research.

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Fig. 1.
(a) Location of megacities in India, 2001. (b) 113 sampling sites in Delhi and its environs, 2003.

Fig. 2. Photometric and gravimetric estimate of PM_{10} at CPCB monitoring station at ITO, Delhi, August–November 2003.

Fig. 3.
Collocating 5 km AOD and PM_{2.5} estimate at point location.

Fig. 4. Interpolated surfaces of $PM_{2.5}$ and 5 km AOD, October–November 2003.

Fig. 5. (a) AOD- $\text{PM}_{2.5}$ distribution disaggregate analysis—same AOD for all points within the same 5 km pixel. (b) 5 km AOD and average $\text{PM}_{2.5}$ at 5 km pixel.

Table 1
Descriptive statistics—PM_{2.5}, PM₁₀, AOD at 5 and 10 km spatial resolutions

Statistical parameter	PM _{2.5} (µg m ⁻³)		PM ₁₀ (µg m ⁻³)		AOD (5 km) ^a		AOD (10 km)	
	Delhi	Outside Delhi	Delhi	Outside Delhi	Delhi	Outside Delhi	Delhi	Outside Delhi
Minimum	30.5	70.0	117.7	172.1	0.548	0.549	0.611	0.603
Mean	82.9	95.7	304.2	466.5	0.647	0.612	0.662	0.636
Maximum	268.4	167.8	850.3	957.9	0.714	0.685	0.693	0.680
S.D.	38.8	26.9	148.4	229.7	0.038	0.051	0.019	0.031
Skewness	1.8	1.5	1.3	0.6	-0.509	0.334	-0.613	0.369
Kurtosis	7.7	5.0	4.5	2.6	2.415	1.511	2.636	1.343
Coefficient of variation	46.9	28.1	48.8	49.2	5.9	8.3	2.9	4.8

^a Aggregate AOD estimates were assigned to 113 monitoring sites.

Table 2

Distance from the city center and the distribution of AOD and PM

	AOD			PM		
	Distance from the city center (decimal degree)					
	5 km spatial resolution		10 km spatial resolution	No. of sites		PM ₁₀ (µg m ⁻³)
	N	Mean	n	Mean		
0.1	13	0.664±0.040	3	0.687±0.169	47	75±7.5
0.2	39	0.649±0.028	10	0.673±0.048	59	99±16.8
0.3	63	0.600±0.020	16	0.634±0.029	7	103±37.6
0.4	89	0.576±0.018	22	0.633±0.025		NA
0.5	127	0.545±0.013	62	0.623±0.012		NA
Inside Delhi	55	0.640±0.023	23	0.657±0.025	98	82.9±7.8
						304.2±29.8

Regression of PM_{2.5} on AOD, mean sea-level pressure and relative humidity at 5 km pixel resolution: point/disaggregate-level analysis—same AOD value was assigned to all points within the 5 km AOD pixel

Table 3

PM _{2.5} as a function of	Interval across satellite crossing time (h:min)										
	0:15	0:30	0:45	1:00	1:15	1:30	1:45	2:00	2:15	2:30	All
ln(AOD)	0.43 (2.77)**	0.449 (3.70)**	0.521 (5.05)**	0.491 (5.35)**	0.497 (5.62)**	0.451 (5.61)**	0.427 (5.41)**	0.419 (5.56)**	0.401 (5.33)**	0.398 (5.17)**	0.398 (5.18)**
Relative humidity (%)	0.024 (1.97)*	0.014 (−1.72)	0.012 (−1.87)	0.011 (−1.85)	0.018 (3.31)**	0.019 (4.51)**	0.019 (4.92)**	0.02 (5.48)**	0.021 (6.05)**	0.023 (6.59)**	0.024 (6.65)**
Mean sea-level pressure (hPa)	0.075 (3.37)**	0.072 (4.42)**	0.07 (5.09)**	0.063 (5.07)**	0.066 (5.71)**	0.067 (6.12)**	0.065 (6.13)**	0.067 (6.74)**	0.066 (6.68)**	0.07 (6.84)**	0.07 (6.85)**
Constant	−72.9 (3.21)**	−69.5 (4.18)**	−66.8 (4.80)**	−59.6 (4.75)**	−63.7 (5.39)**	−64.1 (5.79)**	−62.4 (5.79)**	−64.4 (6.39)**	−63.8 (6.34)**	−67.2 (6.51)**	−67.2 (6.52)**
Observations	129	231	347	423	515	589	652	708	745	760	762
Number of AOD pixels	74	104	141	164	191	210	226	237	246	248	248
Pixel R ²	0.76	0.76	0.71	0.74	0.73	0.72	0.72	0.74	0.75	0.70	0.70

Robust *t* statistics in parentheses.

* Significant at 5%.

** Significant at 1%.

Regression of PM_{2.5} on AOD, mean sea-level pressure and relative humidity at 5 km pixel resolution: aggregate/pixel-level analysis—PM_{2.5} data were averaged to match the spatial resolution of AOD data

Table 4

PM _{2.5} as a function of	Interval across satellite crossing time (h:min)										
	0:15	0:30	0:45	1:00	1:15	1:30	1:45	2:00	2:15	2:30	All
ln(AOD)	0.458 (3.23) **	0.482 (3.66) **	0.454 (4.24) **	0.369 (4.29) **	0.366 (4.46) **	0.371 (4.85) **	0.336 (4.77) **	0.333 (4.61) **	0.342 (4.93) **	0.352 (4.98) **	0.352 (4.99) **
Relative humidity (%)	0.037 (3.62) **	0.012 (31.16)	0.01 (31.32)	0.012 (31.86)	0.013 (2.09) *	0.015 (2.72) **	0.017(3.37) **	0.019 (3.98) **	0.016 (3.80) **	0.016 (3.66) **	0.016 (3.66) **
Mean sea-level pressure (hPa)	0.029 (31.57)	0.054 (3.21) **	0.054 (4.06) **	0.052 (4.67) **	0.051 (4.86) **	0.051 (5.30) **	0.046 (4.92) **	0.047 (5.17) **	0.046 (5.11) **	0.047 (5.10) **	0.047 (5.10) **
Intra-pixel PM _{2.5} variance	0.205 (10.77) **	0.178 (8.30) **	0.158 (9.40) **	0.144 (9.99) **	0.166 (11.27) **	0.173 (12.12) **	0.167 (12.36) **	0.159 (12.53) **	0.156 (12.65) **	0.162 (13.17) **	0.162 (13.15) **
Constant	327.198 (31.46)	351.383 (3.02) **	351.683 (3.82) **	349.588 (4.39) **	348.25 (4.58) **	348.432 (5.01) **	343.471 (4.63) **	344.843 (4.88) **	343.664 (4.80) **	344.513 (4.80) **	344.525 (4.80) **
Observations	37	58	94	109	126	142	155	167	174	175	175
R ²	0.81	0.66	0.61	0.61	0.62	0.63	0.62	0.61	0.6	0.61	0.61

Robust *t* statistics in parentheses.

* Significant at 5%.

** Significant at 1%.