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High resolution aerosol data from MODIS satellite for urban air quality studies

Research Article

A. Chudnovsky[1,2]*, A. Lyapustin[3]†, Y. Wang[4]‡, C. Tang[1]§, J. Schwartz[1]¶, P. Koutrakis[1]**

1   Department of Environmental Health, Harvard School of Public Health, Boston, MA, USA

2   Department of Geography and Human Environment, Tel-Aviv University, Israel, Tel: +972-3-6407049

3   GEST / UMBC, NASA Goddard Space Flight Center, Baltimore, MD, USA

4   University of Maryland, Baltimore County, Baltimore, MD, USA

Abstract: The Moderate Resolution Imaging Spectroradiometer (MODIS) provides daily global coverage, but the 10 km resolution of its aerosol optical depth (AOD) product is not suitable for studying spatial variability of aerosols in urban areas.   Recently, a new Multi-Angle Implementation of Atmospheric Correction (MAIAC) algorithm was developed for MODIS which provides AOD at 1 km resolution.   Using MAIAC data, the relationship between MAIAC AOD and $PM_{2.5}$ as measured by the 27 EPA ground monitoring stations was investigated. These results were also compared to conventional MODIS 10 km AOD retrievals (MOD04) for the same days and locations. The coefficients of determination for MOD04 and for MAIAC are R^2 =0.45 and 0.50 respectively, suggested that AOD is a reasonably good proxy for $PM_{2.5}$ ground concentrations. Finally, we studied the relationship between $PM_{2.5}$ and AOD at the intra-urban scale ($\leqslant$10 km) in Boston.   The fine resolution results indicated spatial variability in particle concentration at a sub-10 kilometer scale.   A local analysis for the Boston area showed that the AOD-$PM_{2.5}$ relationship does not depend on relative humidity and air temperatures below ~7 °C. The correlation improves for temperatures above 7 – 16 °C. We found no dependence on the boundary layer height except when the former was in the range 250-500 m.   Finally, we apply a mixed effects model approach to MAIAC aerosol optical depth (AOD) retrievals from MODIS to predict $PM_{2.5}$ concentrations within the greater Boston area.   With this approach we can control for the inherent day-to-day variability in the AOD-$PM_{2.5}$ relationship, which depends on time-varying parameters such as particle optical properties, vertical and diurnal concentration profiles and ground surface reflectance.   Our results show that the model-predicted $PM_{2.5}$ mass concentrations are highly correlated with the actual observations (out-of-sample R^2 of 0.86). Therefore, adjustment for the daily variability in the AOD-$PM_{2.5}$ relationship provides a means for obtaining spatially-resolved $PM_{2.5}$ concentrations.

Keywords: Remote Sensing • $PM_{2.5}$ exposure assessment • urban air quality • Aerosol Optical Depth • MODIS • MAIAC • mixed effects model.

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*E-mail: achudnov@hsph.harvard.edu, achudnov@post.tau.ac.il
†E-mail: alexei.i.lyapustin@nasa.gov
‡E-mail: yujie.wang-1@nasa.gov

§E-mail: cht710@mail.harvard.edu
¶E-mail: joel@hsph.harvard.edu
**E-mail: petros@hsph.harvard.edu

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1. Introduction

The adverse health effects from particulate matter (PM) pollution with aerodynamic diameter $\leqslant$ 2.5 μm ($PM_{2.5}$) must be considered in developing policies to improve air quality [1]. Substantial epidemiologic literature has demonstrated that exposure to ambient particulate matter (PM) is associated with increased morbidity and mortality, particularly associated with cardiopulmonary disease [2, 3] and lung cancer [3, 4]. Since PM is created by various anthropogenic and natural sources with vastly different atmospheric residence times, it has a high spatio-temporal variability. An accurate assessment of this variability is important as it leads not only to stronger associations between exposure and health but also to deeper understanding of epidemiological time-series studies [5, 6].

Routine measurements of ground-level $PM_{2.5}$ concentrations by air quality monitoring networks are of great importance in assessing exposures, but their spatial coverage has been limited. However, recently it has become clear that satellite remote sensing can be an important tool to complement the ground level measurements. The relevant satellite-derived parameter is the aerosol optical depth (AOD) which quantifies the extinction of solar radiation at a given wavelength due to presence of aerosols in an atmospheric column. Because the satellite-derived AOD is a measure of how much light is absorbed/scattered by particles in the column that are affected by ambient conditions (e.g., variable humidity and consequently variable amounts of water adsorbed on particles), while $PM_{2.5}$ mass is a measure of dry particles near the surface, these two parameters are not expected to be strictly correlated. Furthermore, to be used for air quality applications, including health studies, the satellite retrieved AOD data (e.g. a total column optical measurement) must be converted to estimates of $PM_{2.5}$ concentrations (e.g. a surface-level particulate mass measurement). This type of analysis requires $PM_{2.5}$–AOD collocated pairs which itself is a restrictive requirement [7].

Until recently, the main source of global satellite aerosol data was the MODIS satellite MOD04 algorithm, which provides data at a 10 km resolution. Recently, a new Multi-Angle Implementation of Atmospheric Correction (MAIAC) algorithm was developed for MODIS which provides aerosol information at 1 km resolution [8, 9]. We started with a direct comparison between MOD04 and MAIAC retrievals. Toward this end, we conducted a multi-year analysis to study the relation of same-day/same-location AOD vs $PM_{2.5}$ (2002 – 2008) in the southern part of New England. In addition, we conducted a multi-year analysis by breaking down AOD vs $PM_{2.5}$ regressions by season (spring, summer, fall, winter) and by site location.

Furthermore, we studied the intra-urban (at scales less than 10 km) variability of the relationship between $PM_{2.5}$ and AOD for Boston. Finally, we explored whether it was possible to obtain accurate estimates of $PM_{2.5}$ concentrations using a MAIAC AOD retrieval and mixed effects model approach (daily adjustment for AOD vs $PM_{2.5}$ relationship). Our goal was to show how variability in the AOD vs $PM_{2.5}$ relationship can be captured by a statistical model during one year of data (January 1 through December 31, 2003).

1.1. Ground level $PM_{2.5}$ observations

Twenty-four hour-integrated $PM_{2.5}$ concentrations were measured at 26 U.S. Environmental Protection Agency (EPA) $PM_{2.5}$ monitoring sites during 2002 – 2008 (Figure 1, highlighted by dots and Table 1). These include 15 sites from Massachusetts (MA) and 11 sites from Connecticut (CT). Sampling frequency differed by site and included samples collected every day, every third day, and every sixth day. Additionally, we used 24 hour-integrated $PM_{2.5}$ concentrations from the Harvard School of Public Health (HSPH) supersite located near downtown Boston. Data from this site have been used in a large number of epidemiological studies to assess the temporal variability of individual and population exposures in the region.
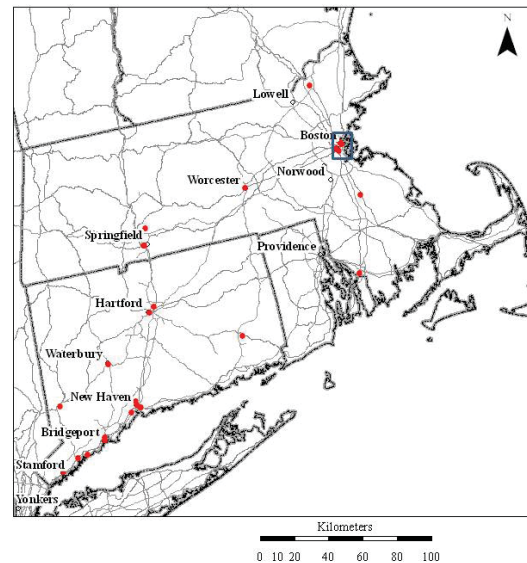
Figure 1. Study area and EPA monitoring sites for New England used for comparison between MOD04 and MAIAC data. Area highlighted by box is the Boston urban domain.

Table 1. EPA ground monitoring sites used in this study over New England. Boston sites are highlighted in italic font.

Site ID	City	Latitude	Longitude
09-001-0010	Bridgeport, CT	41.17	−73.19
09-001-0113	Bridgeport, CT	41.18	−73.19
09-001-1123	Danbury, CT	41.40	−73.44
09-001-2124	Stamford, CT	41.06	−73.53
09-001-3005	Norwalk, CT	41.11	−73.41
09-001-9003	Westport, CT	41.12	−73.34
09-003-1003	E. Hartford, CT	41.78	−72.63
09-003-1018	Hartford, CT	41.76	−72.67
09-009-0018	New Haven, CT	41.29	−72.90
09-009-0026	New Haven, CT	41.29	−72.89
09-009-1123	New Haven, CT	41.31	−72.92
09-009-2008	New Haven, CT	41.33	−72.92
09-009-2123	Waterbury, CT	41.55	−73.04
09-009-8003	W. Haven, CT	41.28	−72.96
09-011-3002	Norwich, CT	41.52	−72.08
25-005-1004	Fall River, MA	41.68	−71.17
25-009-2006	Lynn, MA	42.47	−70.97
25-009-5005	Haverhill, MA	42.77	−71.10
25-013-0008	Chicopee, MA	42.19	−72.56
25-013-0016	Springfield, MA	42.11	−72.59
25-013-2009	Springfield, MA	42.11	−72.60
25-023-0004	Brockton, MA	42.08	−71.01
25-025-0027	*Boston, MA*	42.37	−71.06
25-025-0042	*Boston, MA*	42.33	−71.08
25-025-0043	*Boston, MA*	42.36	−71.05
25-025-0002	*Boston, MA*	42.35	−71.10
25-027-0020	Worcester, MA	42.27	−71.80
Harvard supersite	*Boston, MA*	42.34	−71.10

1.2. Satellite data

A new algorithm MAIAC [8] has been developed to process MODIS data. MAIAC retrieves aerosol parameters over land at 1 km resolution simultaneously with parameters of a surface bidirectional reflectance distribution function (BRDF). This is accomplished by using the time series of MODIS measurements and simultaneous processing of a group of pixels. The MAIAC algorithm ensures that the number of measurements exceeds the number of unknowns, a necessary condition for solving an inverse problem that does not require the assumptions typically used by current operational algorithms. The MODIS time series accumulation also provides multi-angle coverage for every surface grid cell, which is required for the BRDF retrievals from MODIS data. The aerosol parameters include optical depth (total aerosol) and fine mode fraction. Following the MODIS operational aerosol algorithm

(MOD04) [9], models for the fine and coarse aerosol fractions are specified regionally based on the climatology of the Aerosol RObotic NETwork (AERONET) [10] sun-photometer data. AERONET validation over the continental USA showed that the MAIAC and MOD04 algorithms have a similar accuracy over dark and vegetated surfaces, but also showed that MAIAC generally improves accuracy over brighter surfaces, including most urban areas [8]. The improved accuracy of MAIAC resulted from the explicit surface characterization method, in contrast to the empirical surface parameterization approach, utilized in the MOD04 algorithm. Furthermore, MAIAC incorporates a cloud mask (CM) algorithm based on spatio-temporal analysis which augments traditional pixel-level cloud detection techniques [11]. In addition, the residual contamination by clouds and cloud shadows was reduced by discarding 2 pixels adjacent to detected clouds.

In addition to MAIAC data we used daily MODIS Level 2 (MOD04) Collection 5.1 Aerosol data from the Terra platform that are produced at a spatial resolution of 10×10 km^2 (at nadir). More details about the MODIS AOD retrieval are reported in [8, 12]. We conducted a comparative analysis of AOD between MAIAC and the respective MOD04 product. It is important to mention that the MOD04 product is reported for an area of 20 by 20, 500 m pixels in the swath format. This area corresponds to spatial resolution of 10×10 km^2 at nadir, however it grows with the scan angle reaching $\sim 20 \times 40$ km^2 at the edge of scan due to the respective growth of the MODIS pixel footprint by a factor of $\sim 2 \times 4$. Conversely, MAIAC provides a uniform 1 km gridded resolution at selected projection regardless of the scan angle. This means that the MAIAC product is under-sampled by a factor of 4 at nadir, considering maximal available spatial information from 500 m pixels, and is oversampled by a factor of 2 at the edge of scan. In this regard, MOD04 data are always under-sampled by a factor of 400. In order to perform a direct MOD04-MAIAC comparison, the area of each MOD04 pixel was approximated by a polygon, and all MAIAC 1 km data fitting this area were averaged.

1.3. Meteorological data

All meteorological variables used in the analysis (temperature, boundary layer and relative humidity) were obtained through the National Climatic Data Center (NCDC) (NCDC, 2010). Only continuous operating stations with daily data running from 2000 to 2008 were used. In addition, we used meteorological data from Boston Logan airport. Grid cells were matched to the closest weather station for meteorological variables.

1.4. Data analyses

We investigated the associations between AOD and $PM_{2.5}$ daily measurements at the sampling sites for the years 2002–2008. We first made a direct comparison between MOD04 and MAIAC retrievals, with a multi-year analysis of AOD vs $PM_{2.5}$ for the same days (2002–2008) and locations (27 EPA monitoring stations) in New England. Using the same data we performed AOD vs $PM_{2.5}$ regression analysis by season (spring, summer, fall, and winter) for each of the three regions. In addition, we conducted AOD vs $PM_{2.5}$ regression analysis by site location.

Next, we analyzed the intra-urban variability in AOD vs $PM_{2.5}$ relationship inside a 10×10 km^2 area of greater Boston containing four EPA ground monitors and the Harvard Supersite. To take into account the variability of the sampling frequency of the EPA stations, only days with at least three available AOD-$PM_{2.5}$ pairs inside a 10×10 km^2 box were selected (Figure 1, highlighted by the polygon). There were a total of 304 days with 3 – 5 observations. In addition, we analyzed $PM_{2.5}$ vs AOD association in relation to $PM_{2.5}$ particle levels, temperature, boundary layer height and relative humidity. Finally, we explored whether it is possible to obtain accurate estimates of $PM_{2.5}$ concentrations using MAIAC AOD retrievals and statistical modeling with a resolution of 1×1 km^2 conducted for Boston, MA in the northeastern part of U.S.

1.5. Mixed effects model approach

In this study we used a mixed-effects model approach that accounts for day-to-day variability. A basic assumption is that the relationship varies daily because it depends on time-varying parameters such as relative humidity, $PM_{2.5}$ vertical and diurnal concentration profiles, $PM_{2.5}$ optical properties and surface reflectance. In a recent paper, we showed that the mixed effects model approach provides higher accuracy and precision in predicting $PM_{2.5}$ concentrations based on the MODIS AOD dataset than a simple regression model [13, 14]. In the present study we use this model approach to predict $PM_{2.5}$ concentrations based on MAIAC AOD retrievals. Consequently, quantitative relationships between $PM_{2.5}$ concentrations measured at the 27 $PM_{2.5}$ monitoring sites and AOD values in their corresponding grid cells were derived. We used the following mixed effects model with random intercepts and slopes (Eq. 1):

$$PM_{ij} = (\alpha + u_j) + [(\beta_1 + v_j) \times AOD_{ij}] + S_i + \varepsilon_{ij}(u_j v_j) \sim [(oo), \Sigma_\beta] \quad (1)$$

where PM_{ij} is the $PM_{2.5}$ concentration at a spatial site i on day j; AOD_{ij} is the AOD value in the grid cell cor-

responding to site i on day j; α and u_j are the fixed and random intercepts, respectively; β_1 and v_j are the fixed and random slopes, respectively; $Si \sim N(0, \sigma s2)$ is the random intercept of site i; $\varepsilon ij \sim N(0, \sigma 2)$ is the error term at site i on a day j; and $\Sigma\beta$ is the variance–covariance matrix for the random effects. The AOD fixed effect in the model (Eq. 1) accounts for the effect of AOD on $PM_{2.5}$, which was the same for all study days. The AOD random effects explain the daily variability in the $PM_{2.5}$–AOD relationship. The solution of the mixed model equations is a maximum likelihood, a form of estimation that accounts for the parameters in the fixed-effects structure of the model to reduce the bias in the covariance parameter estimates [15]. Currently, this is the method implemented for the SAS statistical software package (proc mixed).

Finally, $PM_{2.5}$ concentrations for each grid cell on a day j were estimated using the corresponding AOD values as follows:

$$PM_{ij} = (\alpha + u_j) + [(\beta_1 + v_j) \times AOD_{ij}] + \varepsilon_{ij} \quad (2)$$

The fixed and random intercepts, and the fixed and random slopes for each study day were derived previously from Eq. 1. Note that the random estimates for the site term were excluded. In this way AOD values were unbiased and representative of their corresponding grid cell.

We use a cross-validation (CV) approach to evaluate the ability of the model to predict $PM_{2.5}$ concentrations for each pixel in the study area. Thus, the dataset was repeatedly randomly divided into 90% (calibration) and 10% (held-out test) splits. We applied the fitted calibration model to estimate $PM_{2.5}$ for the held-out test set. This "out-of-sample" process was repeated ten times to calculate the cross-validated (CV) R^2 values.
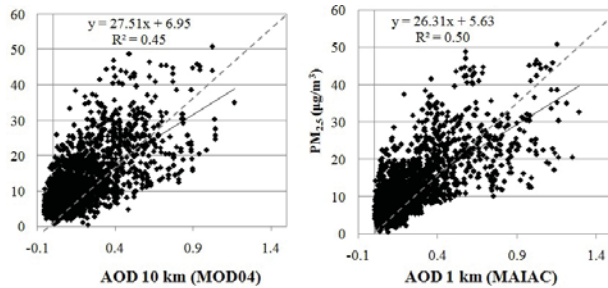
2. Results

2.1. Direct comparison with MOD04 retrieval

This section studies the subset of MOD04/MAIAC data for days when both products are available for a given EPA site. Figure 2 shows the d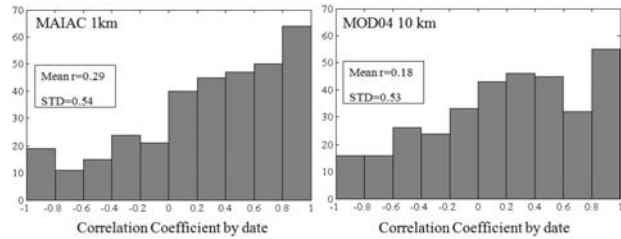irect comparison between $PM_{2.5}$ and AOD for MOD04 (10 km) and MAIAC (1 km) for the same days and locations (2002–2008) in New England (27 locations, N=2310, p<0.0001). The coefficients of determination (R^2) for MOD04 and MAIAC are 0.45 and 0.50 respectively, suggesting that AOD is a reasonably good proxy for $PM_{2.5}$ ground concentrations. In other words, near-surface $PM_{2.5}$ concentrations do not reflect the total AOD column values.

The previous research has shown that the $PM_{2.5}$ vs AOD relationship varies seasonally and by location [16]. Ta-

ble 2 presents a multi-year, seasonal (spring, summer, fall, winter) comparison between MOD04 and MAIAC. Although MAIAC shows intercepts that are lower than those for MOD04, for 8 year of measurements, slopes for both retrievals are similar, with the range of slopes between 7 – 8 µg/m^3 in winter and 26 – 31 µg/m^3 in spring, summer and fall. The slight improvement in correlation is related to the finer resolution of MAIAC with its better correspondence between the monitoring site and the respective grid cell size, and better performance over bright urban areas.

Figure 3. Frequency distribution of daily AOD vs $PM_{2.5}$ correlations.

Figure 2. Comparison between $PM_{2.5}$ and AOD for MODIS 10 km (MOD04) and MAIAC 1 km for the same days and locations (2002-2008) in New England (27 locations, N=2310). The solid line represents the regression line, and the dashed line displays the 1:1 line.

Table 2. Seasonal comparison between coarse MOD04 AOD 10 km and fine resolution MAIAC 1 km AOD for the same days and locations.

Data Source	Statistics	Summer	Fall	Winter	Spring
MOD04	N	786	886	74	564
	Intercept	8.15	7.26	7.41	5.38
	Slope	26.3	28.9	7.7	26.2
	p-value	<.0001	<.0001	0.285	<.0001
	R^2	0.45	0.30	0.002	0.35
MAIAC	N	786	886	74	564
	Intercept	6.08	5.8	7.04	3.56
	Slope	25.3	28.9	8.04	31.9
	p-value	<.0001	<.0001	0.226	<.0001
	R^2	0.50	0.35	0.007	0.41

Figure 3 shows the frequency distribution of the correlation coefficient between $PM_{2.5}$ and AOD by date for 2002-2008, for the same days and sites. In general, both retrievals provide a similar accuracy. Importantly, as can be also seen, the AOD vs $PM_{2.5}$ relationship changes by date for both, MOD04 and MAIAC indicating a clear temporal variation in the association between both parameters. While Figure 3 shows the daily variability in AOD vs

$PM_{2.5}$ relationship, Figure 4 presents correlation coefficients between $PM_{2.5}$ and AOD by the EPA site location for 2002-2008 (the same days were used for MAIAC and MOD04, p<0.005 for all sites). In general, both retrievals provide similar results. Note that the range of correlations for both retrievals across the sites is substantial, which most likely reflects the local meteorological conditions and spatial homogeneity of $PM_{2.5}$, namely how well the local $PM_{2.5}$ measurement can be generalized to the larger footprint of the AOD pixel.
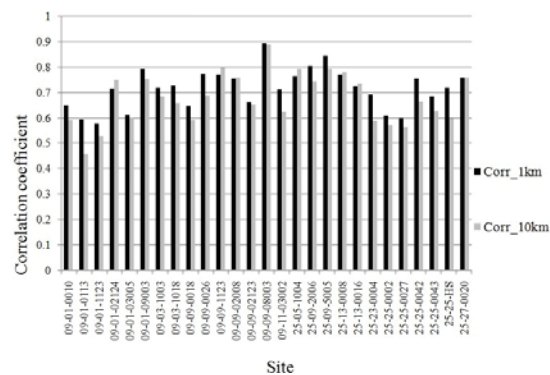
Figure 4. Correlation coefficient between $PM_{2.5}$ and AOD by EPA site location for 2002-2008: dashed line indicates correlation for MAIAC and solid line for MOD04.

2.2. Intra-urban variability in the AOD vs $PM_{2.5}$ relationship

The high resolution AOD potentially carries information about local-scale variability, which is especially important for highly populated urban areas. We define the local variability as the variability in daily averaged $PM_{2.5}$ values among different EPA stations (from 3 to 5) in the 10x10 km^2 box. Figure 5 shows an intra-urban AOD-$PM_{2.5}$ correlation in Boston with R^2 =0.38 for the entire study period 2002 – 2008 (N=304 days). Each $PM_{2.5}$ value for a given station in Figure 5 represents a daily averaged value.
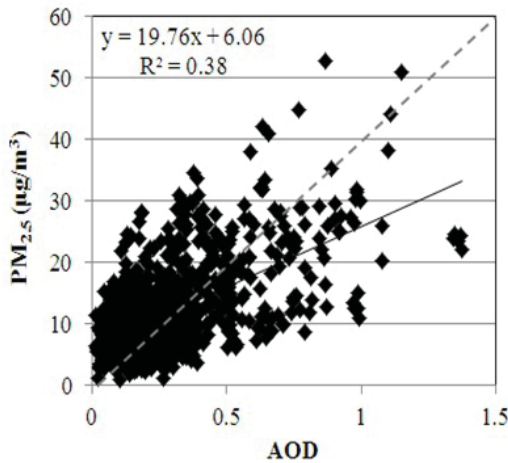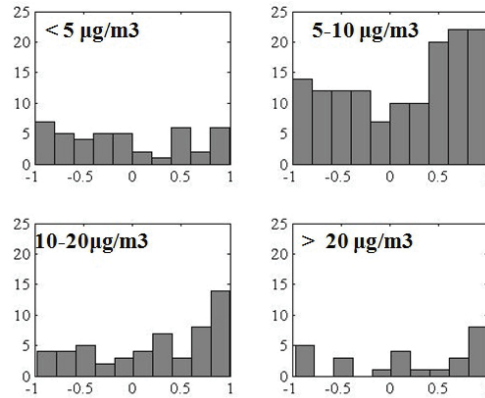
Figure 5. Intra-urban scatter plot between $PM_{2.5}$ at EPA monitoring stations (with at least 3 ground $PM_{2.5}$ measurements) and 1 km MAIAC AOD measured over the entire period 2002-2008 for Boston (N=304 days). The solid line represents the regression line, and the dashed line displays the 1:1 line.

Daily averaged concentrations of $PM_{2.5}$

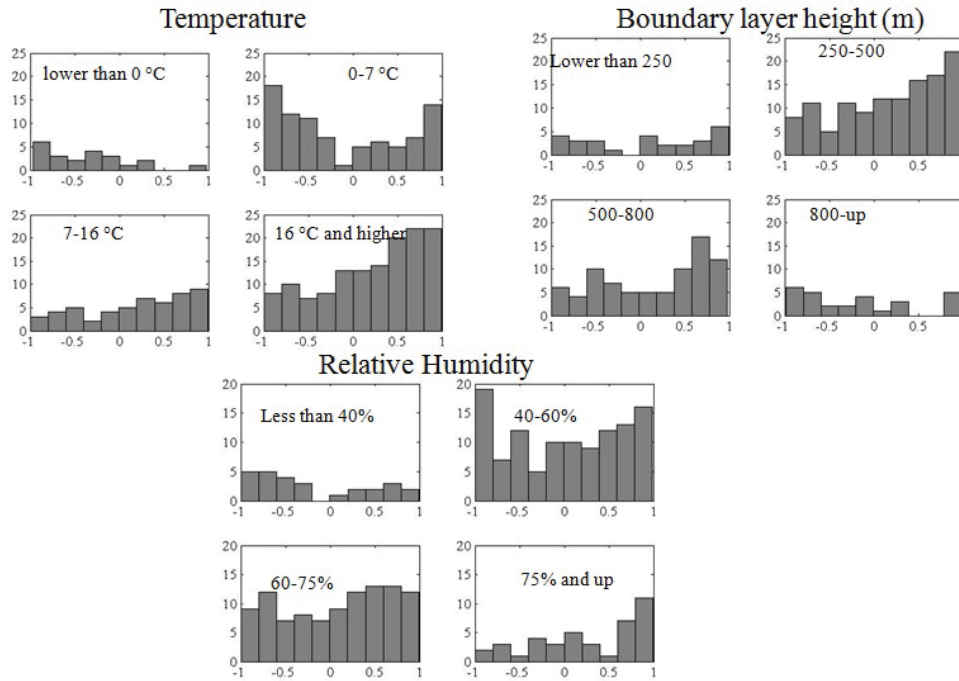**Figure 6.** Correlation coefficient as a function of spatial variability in $PM_{2.5}$ concentrations.

First, we explored an intra-urban AOD-$PM_{2.5}$ correlation during different pollution days, based on EPA observations. Figure 6 shows correlation coefficient by date for different levels of daily averaged $PM_{2.5}$ concentrations. As expected, at low $PM_{2.5}$ levels (<5 $\mu g/m^3$), the distribution of correlation coefficient is almost uniform in the range [−1; 1] indicating low sensitivity of AOD and high relative errors of both AOD and $PM_{2.5}$. The correlation improves at higher $PM_{2.5}$ levels, notably for ranges 5-10 and $10 - 20$ $\mu g/m3$. The correlation seems to decrease at higher PM levels (>20 $\mu g/m3$) which may be an artifact of low sampling statistics.

The intra-urban AOD-$PM_{2.5}$ correlation (Figure 5) includes the temporal meteorological variability for 2002 − 2008. It has been shown that under conditions of a well-mixed boundary layer with low ambient relative humidity (RH), the relationship between $PM_{2.5}$ and AOD may be very robust [17]. With this in mind, in Figure 7a–c we studied the influence of temperature, relative humidity and boundary layer height (BLH) on daily $PM_{2.5}$ vs AOD correlations. Our results do not show any dependence of daily AOD-$PM_{2.5}$ correlations in the Boston metropolitan area on RH and air temperature below 7°C. The correlation improves at higher temperatures, in particular above 7°C typical of late spring–summer–early fall conditions. Figure 7b also shows an improved correlation for the moderate boundary layer heights of $250 - 500$ m, and a poorer correlation outside of this range. Some of these results have a clear physical explanation: for example, the low

temperatures with shallow BLH are associated with winter conditions when average $PM_{2.5}$ and AOD are low and one cannot expect good AOD–$PM_{2.5}$ correlation.

2.3. Prediction of $PM_{2.5}$ concentrations using mixed effect model approach

Since these relationships between AOD and $PM_{2.5}$ measurements vary daily, mixed effects models were used to allow for the regression intercepts and slopes to vary daily. The fixed effects of the AOD intercept and slope were statistically significant: α =9.3 (p<0.0001) and β_1 =17.2 (p<0.0001) respectively. The fixed effects of spatial and temporal predictors were also significant. In addition, the random slopes for AOD by day, and by day and region were both significant (p<0.0001). Figure 8 shows the daily variation of random AOD intercepts and slopes. Note that these results support the findings that because the parameters influencing the relationship between $PM_{2.5}$ and AOD vary from day to day within a given domain, it is necessary to adjust for this daily variability.

The measured and predicted $PM_{2.5}$ concentrations in the cross validation (CV) model are shown in Figure 9. As can be seen, the CV mixed effects model performed quite well. The CV test resulted in a R^2 value of 0.90 and slope of 0.91, indicating a good agreement between the measured and predicted concentrations.

Finally, the model was applied for retrieval days to explore the pattern of $PM_{2.5}$ concentrations on a daily basis. June 25th was selected as the high pollution event to analyze the predicted $PM_{2.5}$ concentrations resulting from the mixed effect model approach. During this day, the average concentrations on EPA monitoring stations in the

Figure 7. Correlation coefficient by date conditioned at several meteorological parameters: a) temperature, b) boundary layer height, and c) relative humidity.
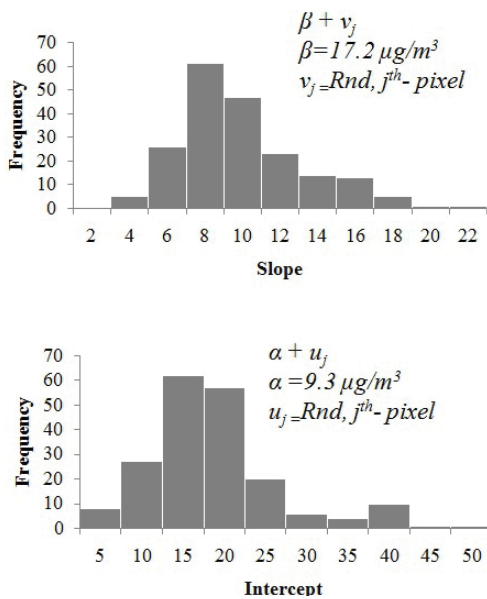
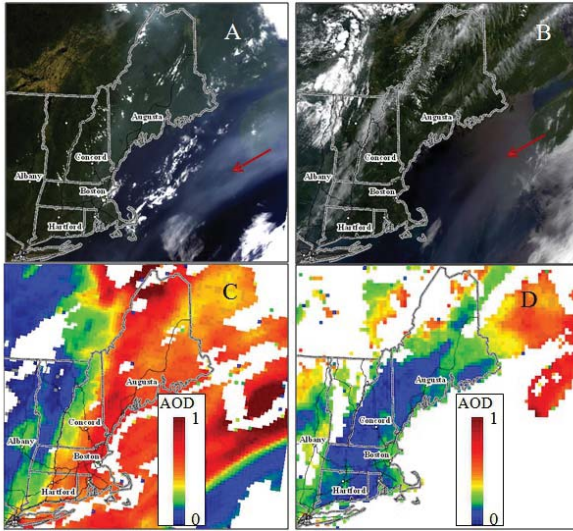**Figure 8.** Frequency distribution of the random intercepts and slopes.
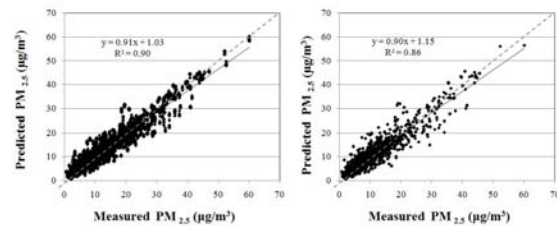
Figure 9. Measured vs predicted PM$_{2.5}$ concentrations for the cross-validation model (left) and the test set (right). The solid line represents the regression line, and the dashed line displays the 1:1 line.

and shows long range transport of thick haze from fires in the Quebec province, Canada on June 24, 2003 (A) and June 25, 2003 (B) (left, red arrow) along the eastern seaboard of the U.S. Figure 9 C and D highlight high AOD values at 550 nm (right) which are elongated with the plum.

In Figure 11 we show the spatial pattern of PM$_{2.5}$ concentrations resulting from the mixed effect model on June 25, 2003. As can be seen, the spatial concentration patterns are different across the domain and are highest in Boston due to high pollution transport from forest fires in Canada. Importantly, as shown in Figure 11, the variability in PM$_{2.5}$ concentrations at fine scale resolution can be high even during high pollution events when the contrast

New England area ranged between 25–42 μg/m3. During 20–24th of June 2003, a forest fire in the Quebec province, Canada, brought smoke pollution into Massachusetts, NE. Figure 10 presents a MODIS Level 1B true-color image

Figure 10. Maps A and B: MODIS Level 1B true-color image shows long range transport of thick haze from fires in the Quebec province, Canada on June 24, 2003 (A) and June 25, 2003 (B) (left, red arrow) along the eastern seaboard of the U.S. Maps C and D: High AOD values at 550 nm (right) are elongated with the plume.
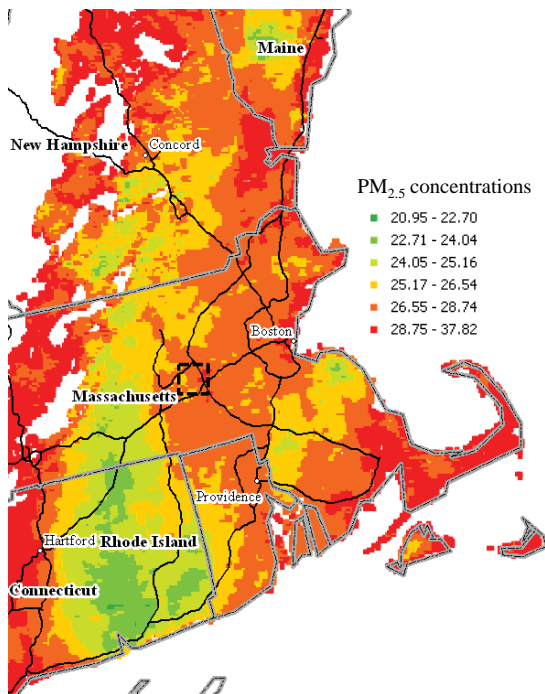
Figure 11. $PM_{2.5}$ concentrations modeled by mixed effects approach for June 25, 2003.

in pollution levels between geographically adjacent areas is not expected to be high. Compare dashed line 1 on Figure 11: for the area of ~20 km, variability in particle concentration ~4 μg/m^3 that can be captured by the model. Furthermore, the fine resolution results indicated spatial variability at a sub-10 kilometer scale.

3. Conclusions

This paper analyzed how the spatial resolution of the AOD product affected the correlation between satellite-retrieved AOD and ground based $PM_{2.5}$ concentrations using 7 years of MODIS Terra observations over the southern part of New England. A direct comparison between coarse MOD04 10 km AOD and high resolution MAIAC 1 km AOD for all collocated AOD–$PM_{2.5}$ pairs for the same days and locations showed that although both retrievals provide reasonable results, MAIAC was found to provide a slightly better correlation. Furthermore, there is clear temporal variation in the association between AOD and $PM_{2.5}$. Importantly, a local analysis for Boston area showed that AOD–$PM_{2.5}$ relationship does not depend on RH and air temperatures below ~7°C. The correlation improves for temperatures above $7 - 16$°C. We found a poorer correlation between AOD and $PM_{2.5}$ on days with very low or very high boundary layer height.

From the epidemiological and exposure assessment point of view, it is of high importance to have information about the spatial variability of the exposures in the city. Several studies published in the last 3 years have shown that high spatial resolution is essential to detect spatial variability in PM levels [18] and in aerosol loadings at regional and at a sub-10 km scale (e.g. intra-urban domain) [19, 20]. Our study using MAIAC data and mixed effect approach showed high accuracy in the New England domain thereby indicating that our model based on MAIAC data can be used to investigate the intra-urban exposure contrasts in $PM_{2.5}$ levels.

Our results show a daily adjustment using a mixed effects model approach effectively controls the combined effects of many parameters that can influence the daily variability in the AOD–$PM_{2.5}$ relationship. This implies that within a given region, the types of aerosols may be more homogeneous and the height of the boundary layer and humidity may be more uniform, making the relationship between AOD to $PM_{2.5}$ less variable. Therefore, the proposed method has the advantage that it can easily be applied to other regions by taking into account the conditions prevailing in each region, and adjusting for daily variability in the AOD vs $PM_{2.5}$ relationship.

Despite promising results, more data need to be processed

and analyzed to understand the full potential and limitations of the high resolution MAIAC AOD product for improving the accuracy in PM$_{2.5}$ estimations. Next, additional parameters can be considered in the model thereby improving the accuracy of PM$_{2.5}$ estimates. Furthermore, in order to further investigate the strengths and limitations of using high resolution satellite AOD data for the routine modeling of PM$_{2.5}$ concentrations during high and low pollution days we are planning to conduct a comprehensive multi-year study based on the full set of MODIS measurements. Next, further improvements to the MAIAC AOD retrieval algorithm would improve accuracy in PM$_{2.5}$ estimation. It is important to emphasize though, that the information content of AOD data alone is limited, and the best results may be achieved by combining different data sources including, for example, the aerosol vertical profile information from satellite or ground-based lidars.

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