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An Improved Method for Monitoring Fine Particulate Matter Mass Concentrations via Satellite Remote Sensing

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ABSTRACT

Ground level monitoring of Particulate Matter (PM) is limited by spatial coverage and resolution, in spite of possessing high temporal resolution and accuracy. Atmospheric Aerosol Optical Depth (AOD), a product of space-borne remote sensing, has shown significant potential for estimating ground level PM concentrations. Several approaches have been used to improve the correlation between AOD-PM by providing corrections for the aerosol vertical profile and ground level humidity. However, the effects of the vertical profile of humidity and aerosol size on the AOD-PM relationship requires further study. In this paper, we propose a method for developing an AOD-$PM_{2.5}$ relationship by retrieving the vertical profile of relative humidity via ground observation data and aerosol size distribution in Beijing. Moreover, a series of Hanel growth coefficients (γ) are applied to determine the specific value, which maximizes the correlation. The results show that applying our proposed method can improve the correlation from R = 0.610 to R = 0.707 for Terra and R = 0.707 to 0.752 for Aqua. The best correlations were obtained for γ = 1.2 and 1.3 for Terra and Aqua, respectively. A good correlation (R = 0.8) between ground based and MODIS based $PM_{2.5}$ measurements, together with employing MODIS to predict true air pollution levels (65% accuracy), suggests that the vertical profile of RH derived via ground level observation and aerosol size should be considered and applied to models in future studies, which utilize satellite data for air pollution monitoring and controlling.

Keywords: Vertical relative humidity; Hygroscopic effect; $PM_{2.5}$; Aerosol Optical Depth; Boundary layer.

INTRODUCTION

In recent years, air pollution has gained remarkable worldwide interest due to the adverse health effect on humans (Caiazzo *et al.*, 2013; Silva *et al.*, 2013). Aerosols, one of the major air pollutants, are groups of solid or liquid particles suspended in the atmosphere (Hinds, 1999; Kondratyev *et al.*, 2006). The components of particles are complex, come in a variety of shapes and sizes and come from multiple sources. They have significant impacts on climate (by modifying the earth's radiation budget or hydrological cycle). Because tiny particles are able to enter the blood circulatory system through our lungs, long term exposure to particles with diameters less than 2.5 µm ($PM_{2.5}$) can cause severe health problems and premature mortality (Chen *et al.*, 2011; Evans *et al.*, 2013; van Donkelaar *et al.*, 2015).

Although many air pollution control policies have been introduced in recent years, China is consistently faced with some of the worst air pollution scenarios in the world, especially in its mega-cities (Kan *et al.*, 2009). As one of these policies, China has started to disclose hourly pollutant concentrations to the public. $PM_{2.5}$ concentrations have been monitored and reported to the public at 496 stations in 74 cities since January 2013. By the end of 2013, hourly $PM_{2.5}$ concentrations were released at more than 850 stations in 161 cities (Lin *et al.*, 2015). In spite of providing data in high temporal resolution, ground-level measurements of $PM_{2.5}$ are restricted by spatial coverage. To compensate for this shortcoming, the use of ancillary technologies and data has been investigated by numerous studies and in different regions (Hoff and Christopher, 2009).

Atmospheric Aerosol Optical Depth (AOD), which is an integral columnar light extinction of atmospheric aerosols, is one of the products of space born remote sensing. Although the main goal of space born AOD is providing information in aerosol radiative forcing on climate and atmospherically corrected land surface reflectance at the global scale (Levy *et al.*, 2007), it has been used to produce seamless, ground-level PM_x mass concentrations (Wang *et al.*, 2010). The use of a Moderate Resolution Image Spectroradiometer (MODIS) on

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board the Terra and Aqua, which is part of NASA's earth observation system (EOS), started a new era of atmospheric aerosol studies, due to its high spectral resolution and almost daily global coverage(monitoring aerosols over specific areas nearly twice per day, at approximately 10:30 and 13:30 local time). The MODIS standard AOD algorithm is comprised of three separate algorithms, which are known as ocean, dark target and deep blue. They provide AOD over oceans, vegetation, dark soil and bright surfaces, such as arid or urban landscapes, respectively. Nadir imaging takes place at a spatial resolution of 10 × 10 km (Kaufman *et al.*, 1997; Hsu *et al.*, 2004; Levy *et al.*, 2010; Shi *et al.*, 2013). Although AOD data can provide valuable information about aerosols at the global scale, finer resolutions are required for studying particulate matter pollution in regional and urban areas (Li *et al.*, 2005a; Paciorek and Liu, 2010). As a result, these algorithms have experienced refinement since MODIS first launched. The latest AOD data is reported at a 3 ×3 km spatial resolution for dark targets and oceans (Levy *et al.*, 2013). In addition, several studies have been conducted, which focused on producing finer resolution AOD by considering restrictions and conditions at the local scale. This was done by modifying surface conditions, followed by utilizing local aerosol models in a look-up table (LUT), or executing an algorithm without a LUT (Lyapustin *et al.*, 2011; Li *et al.*, 2012; Bilal *et al.*, 2013). One of the very first attempts to produce AOD at a 1 × 1 km spatial resolution was conducted by Li *et al.* (2005a) in eastern China. The study was based on a MODIS dark target algorithm (Kaufman *et al.*, 1997), but with more stringent conditions via modification of cloud free conditions and surface reflectance, as well as production of a new look-up table, which was more compatible with local conditions. We use the products of this algorithm to conduct our study.

Monitoring mass concentration of ground level PM_x with AOD is a challenging task. Many works have been conducted to investigate the AOD-PM relationship. Satellite estimated PM_x is particularly essential for regions with lack of ground data (e.g., developing countries). These areas suffer from lack of sophisticated ancillary data monitoring instruments as well. Two variable, empirical, linear regression models have been proposed in many papers (Hoff and Christopher, 2009). However, due to disagreements in correlation coefficients in various regions, it was inferred that other factors such as aerosol vertical structure, humidification, spatial and temporal states, and meteorological conditions have effects on AOD-PM relationship (Chu *et al.*, 2003; Wang, 2003; Paciorek and Liu, 2010). Based on this, complex statistical methods, such as mixed effect models, general additives models (GAM), Bayesian hierarchical models and geographically weighted regression (GWR), together with ground or model based ancillary data, have been used to study AOD-PM (Liu *et al.*, 2009; Tian and Chen, 2010; Lee *et al.*, 2011; Lin *et al.*, 2013). The feasibility of these complex models, generally require more ancillary data, has not been validated, especially in developing countries (Liu, 2013). Moreover, several studies have been conducted by combining global or regional transport chemical models to simulate the key factors affecting the AOD-PM relationships (Liu, 2004; van Donkelaar *et al.*, 2006, 2013). Using this approach, the global mass concentration of $PM_{2.5}$ has been estimated. However, this method is restricted by the uncertainties of the numerical models (Lin *et al.*, 2015). Sophisticated instruments, such as LiDAR, have been used to monitor the vertical structure of aerosols is another approach (Tsai *et al.*, 2011; Chu *et al.*, 2013). Although accurate, LiDAR data are limited and not available in many regions with severe PM pollution.

The development of an AOD-PM relationship has attracted interest from scholars in China, which is a region with remarkable air pollution problems. Li *et al.* (2005b) concluded that AOD-PM_{10} exhibits a better correlation when corrections were made for the mixing layer height and hygroscopic factor over Beijing. In addition, the authors suggested that the Hanel scattering growth coefficient could be expressed as $\gamma = 1.0$. Wang *et al.* (2010) used LiDAR to estimate mixing layer height and AOD at 1 × 1 km. They found the correlation between ground based $PM_{2.5}$ at four stations in Beijing and MODIS estimated $PM_{2.5}$ to be R = 0.68. Song *et al.* (2014) studied the AOD-$PM_{2.5}$ over the Pearl River delta via a general linear regression, semi-empirical model and geographically weighted regression model. The authors cited that the geographically weighted regression model exhibited a better correlation (R = 0.86). The correlation between the Air Quality Index (AQI) and AOD (MOD08) from MODIS was studied by Zheng *et al.* (2014). The correlation between AQI and Aqua deep blue was found to be reasonable (R = 0.65), but for the dark target algorithm, both Aqua and Terra exhibited values of R = 0.43. A back propagation neural networks algorithm was used by Wu *et al.* (2012) to estimate PM concentrations using a combination of satellite data and a set of auxiliary data, including wind speed/direction, mixing height, ground level relative humidity and temperature. In this study, the boundary layer height was collected via a numerical forecast system. The effect of aerosol characteristics (e.g., aerosol chemical composition or size distribution) was investigated by Lin *et al.* (2015) over China. In their study, a humidity correction was made by taking into account the hygroscopic effect, mass extinction efficiency and aerosol size distribution, instead of solely considering Hanel scattering growth coefficient. Moreover, the scale height of aerosol was estimated using visibility data. A value of R = 0.7 was achieved for the correlation between ground based and MODIS estimated $PM_{2.5}$ over Beijing and Tianjin. However Visibility measurements are subjected to some limitations such as human mistakes, also their spatial significance may affected by presence of plums or other occasional heterogeneity. The major shortage of visibility is that it records in discreet numbers (e.g., interval of 1 km for the distances 1 to 10 km away) causing discrepancy in boundary layer height estimating through this method (Lin *et al.*, 2014). Although, aforementioned studies demonstrated relative humidity (RH) to be one of the main factors affecting the AOD-PM relationship, only the humidity impact on the ground level were considered. Considering the role of humidity impact along the vertical direction (vertical profile of RH) could give more appropriate hygroscopic growth factor and scattering growth coefficient (γ). In addition, conventional AOD products contain the light extinction effects of particles of all sizes (both coarse and fine particles).The effect of size distribution should be given additional attention. Therefore, in this paper, the humidity impact along the vertical direction and aerosol size impact will be investigated, respectively.

DATA COLLECTION AND PROCESSING

Satellite Data

This study used the AOD data from MODIS onboard Terra and Aqua. Because AOD is derived in the visible range, only daytime MODIS data (~10:30 Terra and ~13:30 Aqua; local time) was collected. The AOD with fine resolution of 1 × 1 km was retrieved over the Beijing area (~115°–117°E, 39°–41°N) in 2013 (365 days) through the algorithm developed by Li *et al.* (2005a), which is based on dark target algorithm (Kaufman *et al.*, 1997). The Estimated retrieval errors are within 15% to 20% by validation compared with sun-photometer measurements, which is the same accuracy as MODIS standard aerosol products over Beijing and Hong Kong (Li *et al.*, 2005a; Lin *et al.*, 2015). The retrieved AOD (Y) was validated via comparison to AERONET level 1.5 AOD (X), which was observed at the7 AERONET stations located in eastern part of china (3 out of the 7 are located in study area shown in green solid circles in Fig. 1). It exhibited a correlation coefficient of R = 0.79, with a slope of 0.73 and intercept of 0.12 (Lin *et al.*, 2015), which suggests that MODIS AOD correlated well with the sun-photometer observations.

Sun-Photometer Data

One of the objectives of this study is to utilize aerosol size distributions in AOD-PM correlations. AERONET level 1.5 data from ‘Beijing’ (116.381°E, 39.977°N), ‘Beijing CAMS’ (116.317°E, 39.933°N) and ‘Beijing RADI’ (116.379°E, 40.005°N) was collected. Fine Mode Fraction (FMF) data were extracted based on MODIS overpass time and averaged for 3 stations (http://aeronet.gsfc.nasa.gov).

Meteorological Data

By assuming that meteorological conditions do not significantly vary within hundreds of miles over a short period of time (Kumar, 2010), sounding data and surface meteorological parameters, including relative humidity, surface pressure and temperature, were collected from the Beijing radiosonde station (ZBAA,116.58°E, 40.07°N), which was the only available radiosonde station in the study area. The surface metrological data matched with the MODIS overpass time. The station conducts twice daily radiosonde observations at 8:00 AM and 8:00 PM local time, respectively. The morning sounding data (8:00 AM) was collected for further analysis.

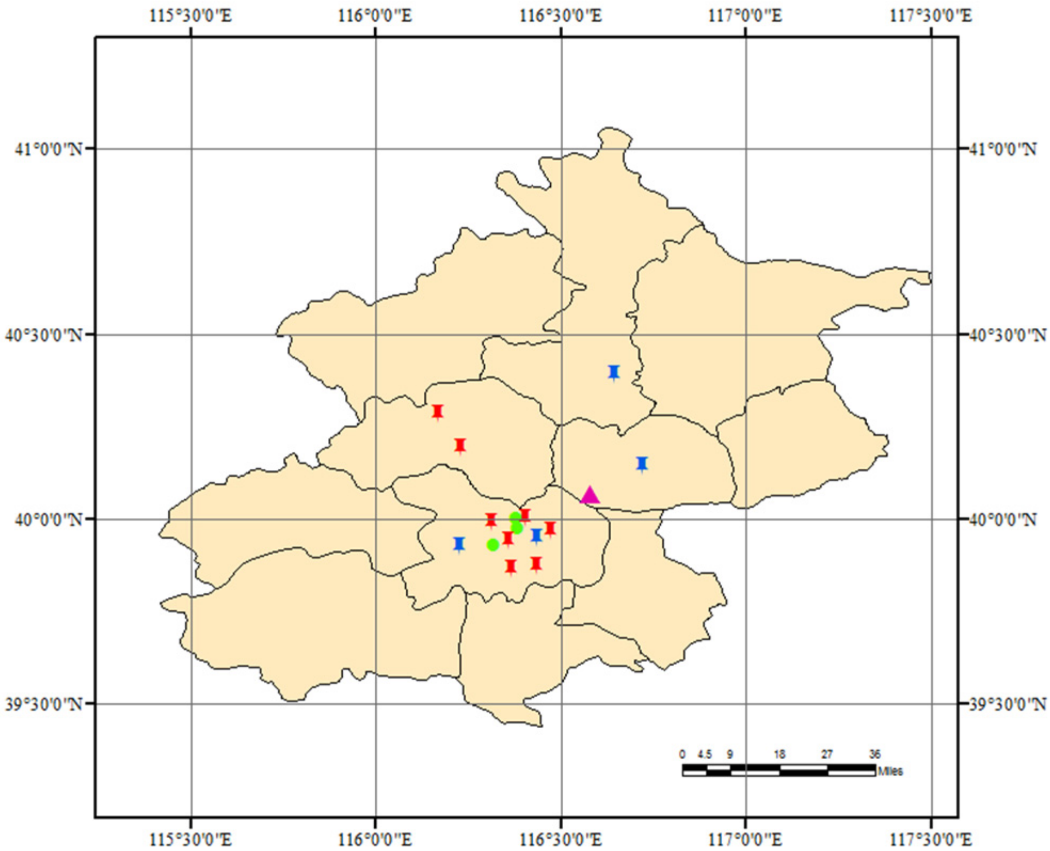

Fig. 1. Spatial distribution of 3 sun-photometer (green), meteorological (purple), 8 ground $PM_{2.5}$ (Red pin) and 4 controlling $PM_{2.5}$ (Blue pin) stations in the Beijing metropolitan area.

Ground Level $PM_{2.5}$

This study used hourly $PM_{2.5}$ concentration data from January 1_{st} to December 31_{st}, 2013. $PM_{2.5}$ concentrations were monitored using the tapered element oscillating microbalance (TEOM) technique or beta attenuation monitors (BAM or β-gauge). Data were recorded every hour, and met the control limit of 10% both for accuracy and precision (EPD, 2013). There are 12 stations located within the Beijing metropolitan area. Fig. 1 illustrates the study area and the location of different meteorological (purple triangle), $PM_{2.5}$ (blue & red pins) and sun-photometer (green solid circle) stations in the study area.

METHODOLOGY

Estimation of Maximum Mixing Height from Morning Temperature Sounding

As previously mentioned, properly constraining the Planetary Boundary Layer (PBL) height is an important part of the AOD-PM correlation process. The PBL is defined as the lowest layer of the atmosphere connected to the earth's surface. Mixing Layer Height (MLH) is the main part of PBL at daytime which is the height up to where because of the thermal structure of the PBL vertical dispersion of air pollutants occur (Emeis *et al.*, 2008). Although LiDAR can provide an accurate estimation of MLH, LiDAR stations are yet not available for many regions, especially those suffering from air pollution in developing countries. Therefore, we evaluate the feasibility of deriving MLH from morning sounding data. This method which is known as parcel method was propose by Holzworth (1964). Note that the MLH that results from this method is known as the maximum mixing height (MMH), which is the maximum height in daytime course up to which atmospheric properties or substances originating from the earth's surface or formed within this layer are nearly uniformly dispersed. This height commonly used in air pollution and dispersion studies to estimate the dilution of a pollutant released within the boundary layer (Seidel *et al.*, 2010). The products from this method were also compared with LiDAR detection in Hong Kong that shows small bias and very similar diurnal changes (Yang *et al.*, 2013). If a dry parcel of air rises adiabatically (changing physical state, without heat additions or withdraws) it begins cooling, while its volume and pressure increase and decrease, respectively (Wallace and Hobbs, 2006). The temperature of this dry parcel can be estimated at different heights using Eq. (1).

$$T_H = T_S + (\Gamma \times H) \tag{1}$$

where T_H is the temperature of a dry air parcel at a specific height. T_s is the surface temperature and "Γ" is the dry adiabatic lapse rate, which is equal to –9.8 °C km^{-1}. H is the height (km) at which temperature is required. This dry parcel of air continues to rise until its temperature is in equilibrium with its surrounding environment (Reible, 1998). To estimate MLH, some general assumptions should be made. First, changes in the vertical temperature profile in the free atmosphere between the sounding time and MLH estimation time are neglected (here 8:00, 10:30 and 13:30). Second, the MLH depends on vertical temperature structure, which is derived from morning temperature sounding and surface temperature at the specific time of estimating mixing height. Additional factors, such as vertical wind shearing, advection, mechanical turbulence and others, are insignificant (Holzworth, 1964). The parcel methods are the most reliable one for detection of convective MLH and air quality studies tend to favor the mixing height based on parcel method (Seibert *et al.*, 2000; Seidel *et al.*, 2010). Based on the above explanation, MLH is the height at which the morning sounding profile and ascending temperature profile in the well-mixed atmospheric boundary layer (derived via Eq. (1) from the surface temperature) intersect each other. In this study, the morning sounding profile and surface temperature at the MODIS overpass time, as well as the daytime maximum surface temperature, were processed to yield diurnal mixing heights for all of 2013.

Vertical Hygroscopic Growth Correction

To prevent the interface of particulate matter with water vapor or condensation in the ground level instruments, PM mass concentrations were measured in a dry state. Consequently, in AOD-PM correlation studies, humidity corrections should also be considered. In previous studies, $PM_{2.5}$ concentrations were corrected only considering the humidity impact on ground level. In this paper, instead of solely considering ground level RH, we account for the vertical distribution of RH in the boundary layer. Based on Bolton (1980), the saturated vapor pressure (hPa) is estimated by:

$$e_s(t) = 6.112 \times \exp\left(\frac{17.67t}{t + 243.5}\right) \tag{2}$$

where e_s is the saturated vapor pressure (hPa), which is influenced by the temperature at different boundary layer altitudes. t is temperature (°C), which is computed by taking into account the surface temperature and dry adiabatic lapse rate at different altitudes. From Eq. (2), and by knowing the pressure in different atmospheric layers, the saturated humidity (q_s) can be derived through Eq. (3).

$$q_s(t) = \frac{\varepsilon \times e_s(t)}{p} \tag{3}$$

P is the pressure at different levels (hPa), which is derived from the morning sounding profile. ε is a constant and equal to 0.622. By assuming that the boundary layer is well-mixed, the specific humidity (q) remains unchanged (Wallace and Hobbs, 2006). Therefore, by calculating RH and q_s at ground level, specific humidity is derived. Consequently, the vertical distribution of RH_V can be estimated.

$$RH_v = q/(q_s(t)) \tag{4}$$

Pervious airborne and ground level studies have shown that the majority of the atmospheric particles are concentrated in the PBL (Liu *et al.*, 2005). Therefore, the integral form of AOD within the boundary layer can be approximated based on Eq. (5).

$$AOD \approx \int_{G}^{MLH} \beta_{0aDRY} \times f(RH)\, dz \tag{5}$$

where β_{0aDry} is the dry aerosol extinction coefficient at the surface level and f(*RH*) is the hygroscopic growth factor, defined by Hanel (1976) as the ratio of the radius of wet aerosol particles to its dry state, which is influenced by particle chemical composition. In this study, we considered the hygroscopic growth factor to be:

$$f(\mathrm{RH}) = (1 - \frac{RH}{100})^{-\gamma} \tag{6}$$

where γ is the growth coefficient (empirical fit coefficient), which is related to aerosol type (Chu *et al.*, 2013). The dry aerosol extinction coefficient is proportional to the dry mass of $PM_{2.5}$ ($PM_{2.5} \propto \beta_{0aDry}$), which is measured by TEOM at ground level (Wang *et al.*, 2010). As a result of the well-mixed boundary layer assumption, the dry aerosol extinction coefficient remains constant in this layer. Consequently, unlike the conventional method, which considers the MLH and hygroscopic correction $f(RH_G)$ based on relative humidity at the ground level (Eq. (7)), we approximate the relationship between $PM_{2.5}$ and AOD based on the vertical profile of relative humidity in the AOD-$PM_{2.5}$ correlation, per Eq. (8).

$$PM_{25} \cdot (MLH \cdot f(RHG)) \propto AOD \tag{7}$$

$$PM_{25} \cdot \int_{G}^{MLH} f(RH_v)\, dz \propto AOD \tag{8}$$

where $f(RH_V)$ are the hygroscopic growth factors based on ground level values and a vertical *RH* profile of *RH* at different levels. *Dz* is the distance in km between two adjacent pressure layers, as determined by the morning sounding profile.

RESULTS

Mixing Layer Height via Morning Sounding

Fig. 2, illustrates the monthly averaged mixing layer height at the MODIS overpass time overhead Beijing (11:00 and 13:00 local time). In addition, we calculated the MLH based on the day time maximum surface temperature. As expected, the maximum boundary layer height occurred when the daytime surface temperature reached a maximum level. Therefore, surface temperature has a direct effect on MLH, and higher surface temperatures, result in higher MLH for the same vertical temperature profile. Because the sounding data were not available for all days in February, we did not show the February results in Fig. 2. The maximum mixing height occurred in spring, reaching nearly 2.3 km in April. Autumn (1.313 km) experienced the next highest mixing height, followed by summer (1.282 km). These results are compatible with the study done by (Cheng *et al.*, 2002), that found the highest MLH occurs in spring and the lowest in winter over Beijing. In addition the author claimed that, parcel method has the best performance comparing with other methods for estimating MLH in Beijing. Although the surface temperature was higher in summer than the other 3 seasons, simultaneously the temperature in the upper atmosphere was also high. Consequently, the rising dry air parcel reached equilibrium with the surrounding environment at a lower altitude. Therefore, the upper air temperature, as derived from morning sounding, is the second term that directly affects MLH derived using this method.

Correlative Analysis of $PM_{2.5}$ and Aerosol Optical Depth

To consider the effect of particle size on the AOD-$PM_{2.5}$ relationship, and because the fine mode AOD (FOD) derived from MODIS is qualitative (Levy *et al.*, 2013), we attained the FMF from sun–photometers 1.5 level data. The FMF value can vary from 0.0 (single coarse mode aerosol) to 1.0 (single fine mode aerosol), and provides quantitative

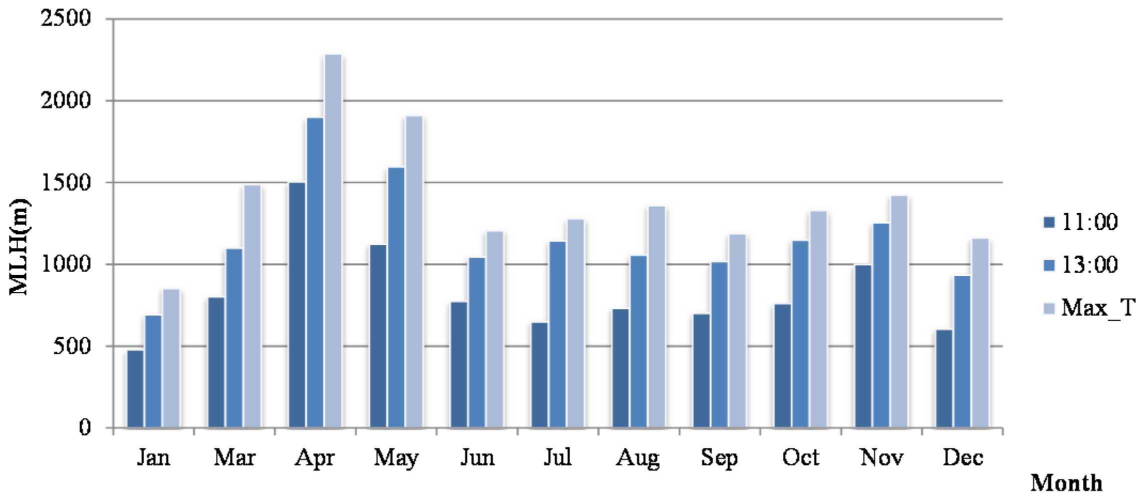

Fig. 2. Monthly averaged MLH over Beijing for 2013.

information on the nature of the aerosol size distribution (Kedia *et al.*, 2014). Detail about AERONET Algorithm (Spectral Deconvolution Algorithm) to retrieve FMF can be found in (O'Neill, 2003). We then multiplied FMF by MODIS derived AOD, resulting in FOD ($FOD = AOD \times FMF$). In Beijing during 2013, the lowest FMF value occurred in spring, which is most likely the result of transported natural dust (due to low humidity in spring and winter) from northwest China, causing the concentration of coarse particles to increase (Liu *et al.*, 2012). In winter, the FMF is higher than spring, which is likely due to local heating systems. Although the role of local emission sources has a remarkable effect on particular matter concentrations (Feng *et al.*, 2014), stable atmospheric conditions, followed by wet weather and higher temperatures during the summer, may have caused the peak FMF value. To estimate the best value of hygroscopic growth coefficient (γ) maximizes the correlation between AOD-FOD and $PM_{2.5}$, we applied a range of (γ) irrespective to the particulate matter chemical composition or aerosol type for both Terra and Aqua (Tables 1 and 2). In addition, to investigate the effect of considering vertical profile of aerosol and RH in AOD-$PM_{2.5}$ correlation, we conducted the linear regression first based on AOD-PM without any ancillary data, secondly through considering MLH and RH value in ground level (conventional).Finally a linear regression model based on vertical profile of RH (vertical RH) is performed. Compared with the original AOD-$PM_{2.5}$, a significant increase in correlation coefficient (R) was observed. The coefficient increased from 0.510 to 0.610 for Terra and 0.589 to 0.707 for Aqua, respectively, when vertical profile and humidity corrections were included in the model. As is shown in Tables 1–2, our proposed method to correct $PM_{2.5}$ data based on the RH vertical profile improves the correlation coefficient, as compared to the conventional method (from 0.610 to 0.671 for Terra and from 0.707 to 0.732 for Aqua). These results demonstrate the importance of considering the *RH* vertical profile for aerosol hygroscopicity corrections. Because the hygroscopic effect modifies the aerosol extinction coefficient, *RH* and *f*(*RH*) are not consistent in MLH. Therefore, considering the vertical profile of *f*(*RH*) is more appropriate when monitoring the vertical discrepancies of AOD due to the inconsistencies of *RH*. For Terra (Table 1), the highest correlation (R = 0.707, 0.671) was achieved with γ = 1.2.For Aqua (Table 2), the maximum correlation (R = 0.752, 0.732) corresponds to γ = 1.3 for the FOD and AOD data sets, respectively. This result is in an acceptable range with previous study done in Beijing and Taiwan with the range of γ equal to 1 and 1.3 respectively (Li *et al.*, 2005b; Chu *et al.*, 2013) The difference between the growth coefficient ranges for Terra and Aqua can be explained by the different sample numbers. In addition, it is likely due to difference in MLH at the Aqua and Terra overpass times, as well as the variations in atmospheric conditions and aerosol compositions. Investigating the influence of aerosol size on the AOD-$PM_{2.5}$ correlation proves that applying

Table 1. Comparing the correlation coefficients (R) between the AOD-PM, conventional method (Eq. (7)) and vertical RH correction method (Eq. (8)) based on different ranges of growth coefficients (γ) and FOD size distributions for Terra (N = 1078)

γ Growth coefficient	R AOD-PM	R Conventional	R Vertical RH	R Conventional with FOD	R Vertical RH with FOD
0.7	0.510	0.600	0.628	0.655	0.679
0.8	0.510	0.604	0.642	0.658	0.687
0.9	0.510	0.608	0.651	0.662	0.692
1.0	0.510	0.610	0.655	0.664	0.698
1.1	0.510	0.610	0.664	0.665	0.702
1.2	0.510	0.609	0.671	0.669	0.707
1.3	0.510	0.602	0.667	0.662	0.700

Table 2. Comparing the correlation coefficients (R) between the AOD-PM, conventional method (Eq. (7)) and vertical RH correction method (Eq. (8)) based on different ranges of growth coefficients (γ) and FOD size distributions for Aqua (N = 933)

γ Growth coefficient	R AOD-PM	R Conventional	R Vertical RH	R Conventional with FOD	R Vertical RH with FOD
0.7	0.589	0.685	0.672	0.680	0.694
0.8	0.589	0.692	0.688	0.699	0.700
0.9	0.589	0.697	0.698	0.703	0.702
1.0	0.589	0.707	0.716	0.712	0.729
1.1	0.589	0.704	0. 724	0.716	0.739
1.2	0.589	0.702	0.728	0.721	0.747
1.3	0.589	0.700	0.732	0.730	0.752
1.4	0.589	0.698	0.729	0.721	0.749

FMF, which was derived from sun-photometers, to MODIS derived AOD can improve the correlation. For the AOD data set, the maximum correlation coefficient reached 0.671 for Terra and 0.732 for Aqua. For the FOD data set, the correlation coefficient reached 0.707 for Terra and 0.752 for Aqua. This is because AOD encompasses the light extinction due to both coarse and fine mode aerosols, in contrast with $PM_{2.5}$, which is classified as fine particulate matter. Therefore, this correlation improvement between FOD, as a fine mode of AOD, and $PM_{2.5}$ is reasonable. Ignoring the differences in sample populations (N), better correlation coefficients were obtained from Aqua. This can be explained by the more homogeneous boundary layer at the Aqua overpass time, versus the Terra overpass time. Fig. 3 shows the linear regression between FOD from Terra and Aqua together, with $PM_{2.5}$, measured at 8 stations in Beijing. It is corrected based on the conventional and new methods proposed in this paper. Both methods exhibited statistically significant correlation ($p < 0.01$), with slopes of 364 and 437, and intercepts of –31 and –38 for the conventional and vertical RH methods, respectively. The highest correlation coefficient R = 0.730 was attained by applying our new

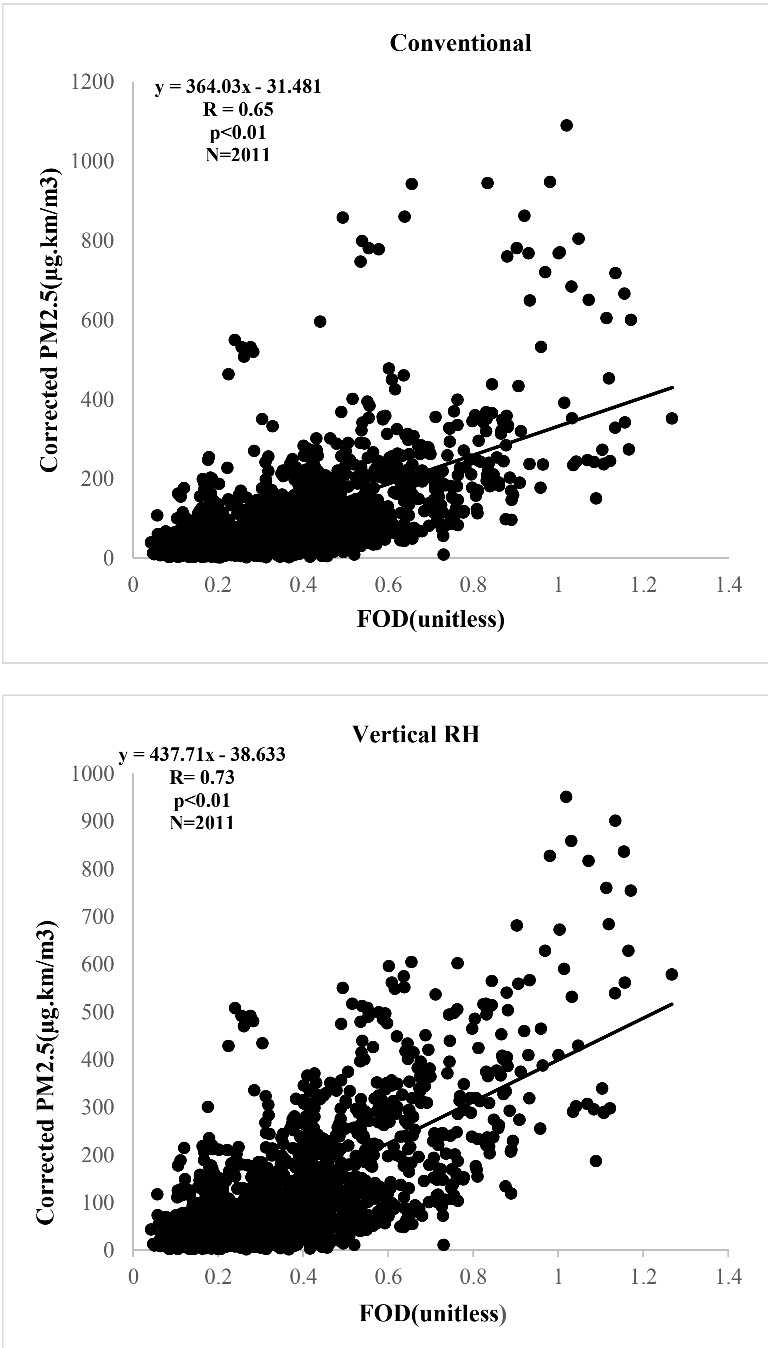

Fig. 3. Correlation between FOD (MODIS Terra and Aqua AOD × FMF) and ground $PM_{2.5}$, which were corrected based on conventional (upper) and our proposed method (lower), respectively.

method. The highest correlation coefficient of the conventional method was R = 0.654. This remarkable improvement in the correlation coefficient demonstrates the importance of taking into account the vertical profile of RH in AOD-$PM_{2.5}$ correlations. Overall, by considering the optimum range of hygroscopic growth coefficients in vertical profile of RH and applying size distributions through considering FMF and *RH* vertical profiles, the correlation coefficient increased from R = 0.610 to R = 0.707 for Terra and R = 0.707 to R = 0.752 for Aqua.

Method Validation

To evaluate our proposed method of ground level $PM_{2.5}$ estimation, we conducted a correlative analysis to compare ground measured and MODIS estimated $PM_{2.5}$ (Fig. 4). The validation data set comprises the twice daily averaged ground level $PM_{2.5}$ measured at four control stations in Beijing (Fig. 1) based on Terra and Aqua overpass times. The AOD was derived over these stations together with FMF were then applied in the regression model to calculate MODIS (Terra and Aqua) based $PM_{2.5}$in accordance with conventional and proposed method explained in this paper. Root mean square error (RMSE) and mean absolute error (MAE) are two common terms used to measure the closeness of predictions to observed values. Based on 298 observations, a high correlation coefficient R = 0.77, RMSE = 37.05 and MAE = 24.5, based on a mean ground level $PM_{2.5}$ of 55.95 µg m^{-3}, prove the capability of using satellite data in ground level $PM_{2.5}$ monitoring, particularly in areas lacking ground level observations. As can be seen, our proposed method is more capable to estimate $PM_{2.5}$ than conventional method. An improvement in RMSE from 42.32 to 37.05, MAE from 28.93 to 24.5 and correlation coefficient from 0.670 to 0.770 (Fig. 4) demonstrate that vertical profile of RH instead of ground level solely should be considered in future $PM_{2.5}$ estimation projects based on satellite remote sensing.

Applicability to Air Quality Monitoring

One of the major goals of $PM_{2.5}$ monitoring is improving air quality and health. Overall, controlling air pollution levels is more beneficial than solely reporting AQI. Therefore, we assess the feasibility of satellite based $PM_{2.5}$ in air quality and air pollution level estimation. Beginning in 2013, the Ministry of Environment Protection (MEP) of the People's Republic of China started reporting air quality in accordance with a new air quality index (AQI). The AQI level is based on six atmospheric air pollutant concentrations, including SO_2, NO_2, CO, O_3, PM_{10} and $PM_{2.5}$. Although AQI is based on daily averaged $PM_{2.5}$ concentrations, our study examined the ability to predict real time air pollution levels based on $PM_{2.5}$ concentrations at the time of MODIS measurements. Table 3 illustrates the air quality and air pollution sub-index level based on corresponding $PM_{2.5}$ concentrations (Zheng *et al.*, 2014).

Observed and estimated $PM_{2.5}$ is used to monitor air pollution levels at the MODIS overpass times. As shown in Fig. 5, in comparison with air pollution levels derived from ground level $PM_{2.5}$, satellite data were able to estimate air pollution levels within approximately 65% of ground $PM_{2.5}$ data. Likewise, satellite data overestimated and underestimated air pollution levels by 19% and 16%, respectively. Table 4 shows the results of true air pollution levels based on $PM_{2.5}$ concentration estimated via satellite data, as compared with ground observations from different months in 2013. Irrespective to the number of samples in different months, April exhibited the highest true air pollution level percentage at 86%.The correlation between the ground based and satellite based air pollution level was R = 0.93. The lowest percentage occurred during the winter (Jan = 47%, Feb = 64% and Dec = 57%). This is likely due to the difficulty of retrieving accurate AOD over Beijing in winter months because of discrepancies in surface reflectance. In general, it can be stated that MODIS is capable of monitoring air

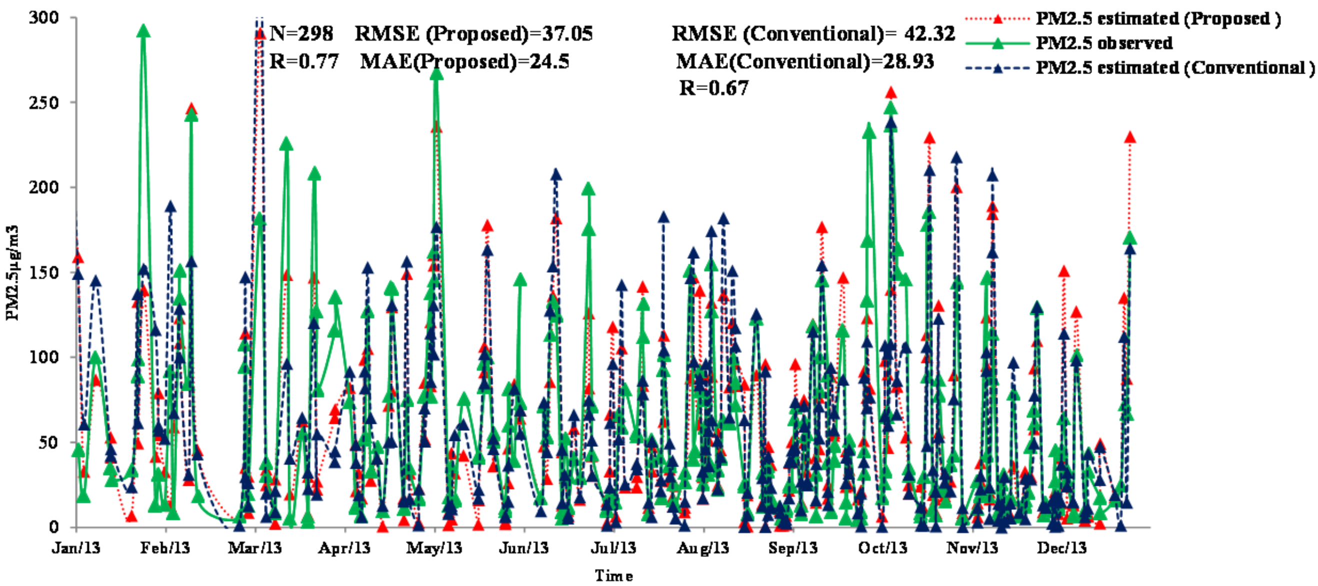

Fig. 4. Comparison of $PM_{2.5}$ observed at the ground level versus estimated by MODIS measurements based on conventional and proposed methods.

Table 3. AQI and air pollution levels with corresponding $PM_{2.5}$ concentrations (Ministry of Environmental Protection of the People's Republic of China).

AQI	Air pollution level	Max $PM_{2.5}$ concentration (μg m^{-3})
50	Good	35
100	Moderate	75
150	Lightly polluted (sensitive group)	115
200	Medially polluted (unhealthy)	150
300	Heavily polluted (very unhealthy)	250
400	Severely polluted	350
500	Severely polluted	500

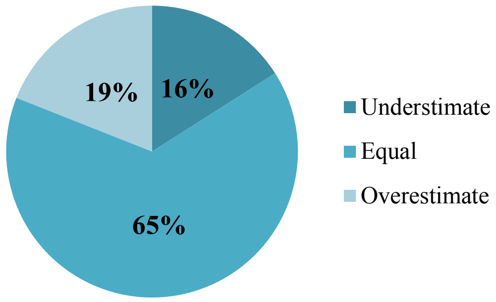

Fig. 5. Feasibility of MODIS for estimating true air pollution levels based on $PM_{2.5}$ concentration compared to ground stations.

Table 4. Monthly variation of the ability of MODIS to estimate true air pollution levels based on $PM_{2.5}$ concentrations.

Month	True air pollution level (%)	Correlation coefficient (r)	Number of samples	p value
Jan	47	0.80	12	< 0.01
Feb	64	0.90	11	< 0.01
March	73	0.85	11	< 0.01
April	86	0.93	14	< 0.01
May	57	0.72	14	< 0.01
Jun	60	0.77	25	< 0.01
July	65	0.60	33	< 0.01
Aug	70	0.72	40	< 0.01
Sep	57	0.76	32	< 0.01
Oct	62	0.70	34	< 0.01
Nov	75	0.81	36	< 0.01
Dec	57	0.72	30	< 0.01

pollution levels based on $PM_{2.5}$ concentration over Beijing during the spring, summer and autumn months.

CONCLUSIONS

In spite of exhibiting high accuracy when measuring ground level $PM_{2.5}$, monitoring stations are sparse and not available in many regions of developing countries. Hence, air pollution monitoring using remote sensing technology has received increasing attention in recent years due to its remarkable spatial coverage. Although previous studies have demonstrated the feasibility of using space-borne AOD to estimate particulate matter concentrations, monitoring can be divided into different categories based on the methods and facilities used when processing data. In general, all studies agree that utilizing the aerosol vertical distribution, relative humidity and size distribution have notable influences on AOD-PM_x correlations.

In contrast with previous studies, which only considered the impact of ground level RH on aerosol hygroscopicity, this study accounted for the vertical RH profile, including the hygroscopic effects on the vertical direction. Moreover, we found highest correlation achieved by applying $\gamma = 1.2$ and 1.3 for Terra and Aqua respectively. To study the importance of size distribution in AOD (integral of light extinction coefficient for both coarse and fine particulates) and $PM_{2.5}$ (fine mode particulate matter), FMF data were derived from sun-photometer stations located in Beijing for 2013. Significant increases in the correlation coefficients (from R = 0.610 to 0.707 for Terra and R = 0.707 to 0.752 for Aqua) were observed when the vertical profiles of RH and FOD were used in regression modeling, through applying appropriate ranges of growth coefficients. Together, Aqua and Terra achieved a correlation coefficient of R = 0.73

using our method, while the conventional method exhibited a correlation coefficient of R = 0.650. This demonstrates the importance of the vertical relative humidity profile and size distribution of the AOD-$PM_{2.5}$ relationship.

To validate our proposed method, we compared satellite based $PM_{2.5}$ values with ground measured $PM_{2.5}$, which exhibited a high correlation coefficient of R = 0.77, MAE = 24.5 and RMSE = 37.05, demonstrating the capability of satellite data to monitor $PM_{2.5}$. In addition, we assessed the feasibility of satellite data for estimating air pollution levels. We found that when using satellite data, 65% of air pollution levels based on $PM_{2.5}$ concentration can be estimated, with best results occurring in April, when 86% of values were well correlated. Although these results demonstrate development of better correlation coefficients, we believe that the availability of more control stations can further verify our method. In conclusion, our proposed method is a practical way to determine the vertical profile of aerosols, particularly in areas with a lack of sophisticated instrumentation, such as LiDAR. Using common meteorology variables (RH, temperature, pressure, sounding and others), more regions can utilize our proposed method to estimate satellite based $PM_{2.5}$ concentrations. However, the proposed method requires the radiosonde data for the MLH estimation and AERONET data for the aerosol fine mode fraction to fit the $PM_{2.5}$ estimation. This is the limitation of the method. Although for the area with lack of AERONET data, our proposed method for deriving vertical profile of *RH* is applicable. Further study is needed to assess the feasibility of the products from weather prediction models and satellite remote sensing to obtain these two parameters in the air quality remote sensing field.

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