Monitoring $PM_{2.5}$ from Past, Present,

by Yang Liu

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Applying satellite remote sensing data in $PM_{2.5}$ exposure assessment and health effects research.

Environmental epidemiologic studies worldwide have established a robust association between exposure to ambient fine particulate matter ($PM_{2.5}$, i.e., airborne particles with an aerodynamic diameter less than or equal to 2.5 µm) and adverse health outcomes, including respiratory and cardiovascular morbidity and mortality.[1] Exposure to ambient $PM_{2.5}$ was recently estimated to be the eighth leading factor of the global burden of disease, contributing 3.2 million premature deaths worldwide in 2010.[2] In addition, the health effects associated with $PM_{2.5}$ exposure have shown no apparent threshold at lower concentrations as they are being detected at typical $PM_{2.5}$ levels in developed countries such as the United States and Canada.[3] On October 17, 2013, the International Agency for Research on Cancer

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(IARC) of the World Health Organization announced that it has classified outdoor air pollution and separately particulate matter (PM), as carcinogenic to humans (Group 1).[4]

Since 1997, $PM_{2.5}$ has been one of the six air pollutants in the United States regulated under the National Ambient Air Quality Standards (NAAQS). Most studies of the associations between $PM_{2.5}$ and health have relied on ground measurements from regulatory monitoring networks, such as the U.S. Environmental Protection Agency's (EPA) Air Quality System to estimate exposure to $PM_{2.5}$. Although ground measurements are considered the most accurate, this approach has two major weaknesses.

First, these monitors are sparsely and unevenly distributed in space. The United States has the most extensive monitoring network in the world, but its approximately 1,200 stations are located in only 30% of the 3,100 counties in the continental United States. For some pollutants and some counties, this coverage is adequate to represent human exposure. Health effects researchers may assign people living within 20–40 km of a $PM_{2.5}$ monitor the same exposure level, even though emissions from traffic and industrial sources can cause substantial heterogeneity in $PM_{2.5}$ levels at finer scales.[5,6] Ignoring within-city contrasts may underestimate the effect of $PM_{2.5}$ exposure on the health outcomes.[7,8]

Second, the limited coverage of ground monitors restricts epidemiological studies to areas near monitoring sites; approximately 30% of the U.S. population lives in suburban and rural counties without any coverage. The composition of rural $PM_{2.5}$ tends to differ from urban $PM_{2.5}$ due to different emission source profiles.[9,10] Compared to ground monitors, a major advantage of satellite data is its broad spatial coverage.

Satellite Aerosol Optical Depth and $PM_{2.5}$

Although satellite remote sensing has been used to track particle air pollution events since the 1970s,[11] most quantitative studies of atmospheric particles began after the launch of NASA's Terra satellite in December 1999. The most robust parameter that current passive aerosol sensors such as the Moderate Resolution Imaging Spectro Radiometer (MODIS), the Multiangle Imaging Spectro Radiometer (MISR), and the Visible Infrared Imaging Radiometer Suite (VIIRS) can readily retrieve is aerosol optical depth (AOD).

AOD is defined as the integral of aerosol extinction coefficients along the entire vertical atmospheric column. As an optical measure of particle abundance, its relationship with ground-level $PM_{2.5}$, assuming a well-mixed boundary layer and no pollution layers aloft, can be expressed as follows[12]

$$PM_{2.5} = \frac{4\rho r_{eff}}{3f(RH)\times Q_{ext,dry}} \times \frac{f_{PBL}}{H_{PBL}} \times AOD = \frac{f_{PBL}}{H_{PBL}} \times \frac{1}{S} \times AOD \quad (1)$$

Where r is particle density (g/m^{-3}); r_{eff} is particle effective radius; $f(RH)$ is the ratio of ambient and dry extinction coefficients; $Q_{ext,dry}$ is particle extinction efficiency; f_{PBL} is the AOD fraction in the boundary layer; H_{PBL} is the boundary layer height; and S is particle specific extinction efficiency (m^2/g^{-1}) at ambient relative humidity (RH).

Equation 1 clearly shows that the $PM_{2.5}$–AOD relationship is a function of particle size distribution, composition, and vertical distribution. Since measurement of these properties is rare, directly applying Equation 1 to estimate $PM_{2.5}$ concentrations using satellite AOD is difficult. Over the past decade, two approaches have been developed to alleviate the data scarcity issue.

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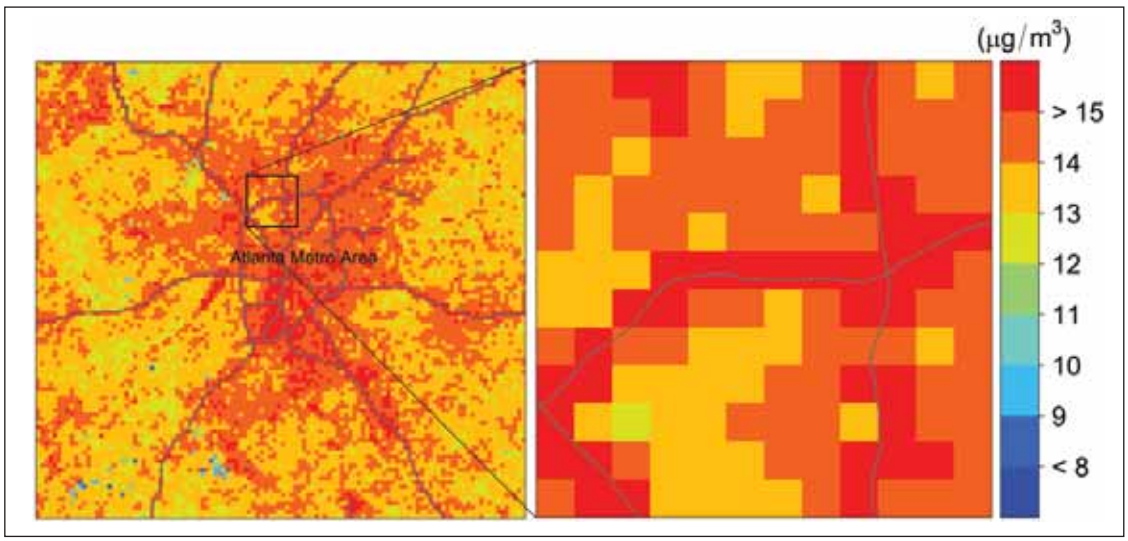

Figure 1. Left: MAIAC estimated annual mean $PM_{2.5}$ levels at 1 km resolution in Georgia, USA, 2003. Right: $PM_{2.5}$ gradient in the 10x10 km^2 box in the left panel.

The first (called the statistical model hereinafter) involves the development of empirical statistical models to estimate $PM_{2.5}$ concentrations with AOD as the primary predictor. Early studies often employed linear correlation and univariate regression as primary analytical tools.[13-15] Soon meteorological and land-use parameters were introduced into the models as covariates to account for changing particle optical and chemical properties.[16,17] For example, the following regression model was proposed to estimate daily $PM_{2.5}$ concentrations in the eastern United States:[16]

$$\ln(PM_{2.5}) = \beta_0 + \beta_1 \times season + \beta_2 \times region + \beta_3 \times distance_to_coast + \beta_4 \times site + \beta_{RH} \times RH + \beta_{PBL} \times H_{PBL} + \beta_{AOD} \times AOD \quad (2)$$

Where *region* is defined as a three-level categorical variable (New England, Mid-Atlantic, and South-Atlantic); *site* is defined as a three-level categorical variable (rural, suburban, and urban); and *distance_to_coast* is defined as a dichotomous variable (≤100km and >100km).

The second approach (called the scaling model hereinafter) relies on atmospheric chemistry models to simulate $\frac{f_{PBL}}{H_{PBL}} \times \frac{1}{S}$ in order to establish the association between AOD and $PM_{2.5}$ using the following equation:[18,19]

$$PM_{2.5} = \frac{Simulated\ PM_{2.5}}{Simulated\ AOD} \times Satellite\ AOD \quad (3)$$

Where an atmospheric chemical transport model (CTM) provides simulated $PM_{2.5}$ concentrations and AOD in each modeling grid cell.

The development of these two approaches up to 2009 was summarized in the 39th Annual A&WMA Critical Review by Hoff and Christopher.[20] Since then, more sophisticated statistical models with non-linear or multi-level structures have been developed to allow the $PM_{2.5}$–AOD relationship to take a non-linear form and to vary in space and time.[21-24] In the meantime, satellite-retrieved land-surface properties and other information have been considered in the scaling model to restrict modeling areas to where satellite AOD and CTM simulations are of sufficiently high quality.[19]

Applications of the Two Approaches

Two factors determine that the statistical models generally have greater prediction accuracy when compared with the scaling model. First and most important, ground $PM_{2.5}$ measurements are used to calibrate the model, which ensures model predictions to have little overall bias. Second, statistical models include land use and meteorological data as covariates and their more flexible structure effectively reduces the impact of the measurement errors in AOD and other variables on model predictions. However, the requirement of extensive ground data support hinders their applications outside only a handful of developed countries. As a result, the primary goal of these models is to provide accurate daily to annual average $PM_{2.5}$ concentration estimates to fill the data gaps left by central monitors.

For example, Figure 1 shows satellite-estimated annual mean $PM_{2.5}$ concentration surface in Georgia using a two-stage spatial statistical model with the

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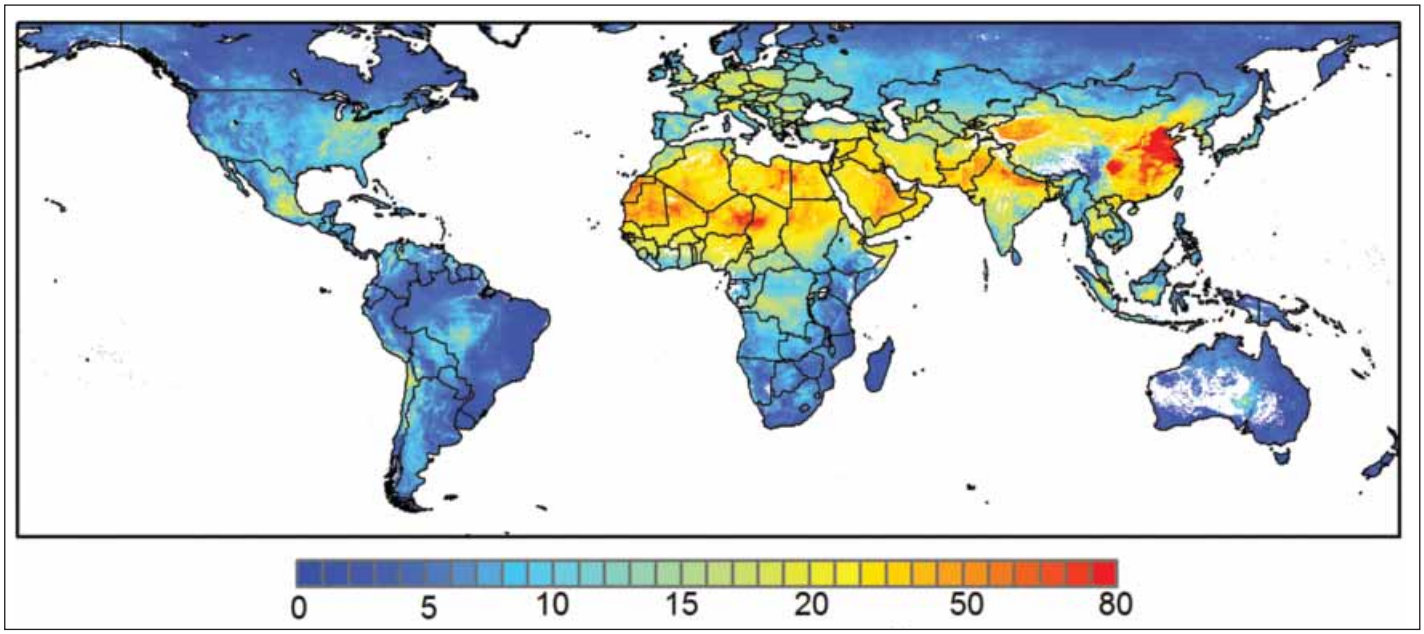

Figure 2. Global satellite-derived mean $PM_{2.5}$ concentrations averaged over 2001–2006.

Multiangle Implementation of Atmospheric Correction (MAIAC) AOD data.[25] This model has a model fitting R^2 of 0.83 and mean fitting error of 1.9 μg/m^3 for daily $PM_{2.5}$ concentration. The detailed spatial texture of the predicted $PM_{2.5}$ surface at 1 km resolution would be of great value to regional air pollution epidemiological studies that have been historically limited to the proximity of central monitors.

The scaling model provides a more straightforward physical basis for relating satellite AOD measurements to the spatial and temporal pattern of surface $PM_{2.5}$ concentrations. Because satellite AOD and CTM results are generally available globally, $PM_{2.5}$ concentrations can be predicted in regions without any ground measurements. For example, Figure 2 shows the global distribution of mean $PM_{2.5}$ concentrations at 10 km spatial resolution averaged between 2001 and 2006.[19] The correlation coefficient over the United States between satellite-estimated long-term average $PM_{2.5}$ concentrations and ground measurements is 0.77. It provides the much-needed coverage over the developing countries with heavy air pollution and sparse or no routine air quality monitoring. However, this great advantage over the statistical models comes at a cost.

Without the calibration of ground $PM_{2.5}$ measurements, the scaling model tends to have higher prediction errors than those from the statistical models. In addition, not being able to include a model intercept partially limits its ability to account for the errors in AOD retrievals and CTM simulations that vary in space and time. Another potential issue is that Equation 3 does not readily produce error statistics (e.g., a 95% confidence interval for predicted $PM_{2.5}$ concentrations), although such information has not yet been widely used in epidemiological studies.

The gap-filling ability of both the statistical and scaling models frees air pollution health effect studies from being limited to areas covered by ground monitoring networks. In the United States, suburban and rural populations, which have been historically underrepresented, have been included in studies linking exposure to $PM_{2.5}$ and acute myocardial infarction and adverse birth outcomes.[26,27] The 2010 Global Burden of Disease project combined satellite data, global chemical transport models, and ground observations to estimate worldwide long-term exposure to ambient $PM_{2.5}$.[28]

To date, a handful of studies have examined the associations between satellite-predicted $PM_{2.5}$ and health outcomes. For example, Madrigano et al. (2013) examined the association between MODIS-based long-term area exposure to $PM_{2.5}$ and acute myocardial infarction (AMI) in Worcester, MA, and reported that an interquartile range (IQR) increase in area $PM_{2.5}$ (0.59 μg/m^3) was associated with a 16% increase in the odds of AMI.[26] Crouse et al. (2012) investigated the association between satellite-based long-term exposure to ambient $PM_{2.5}$ and

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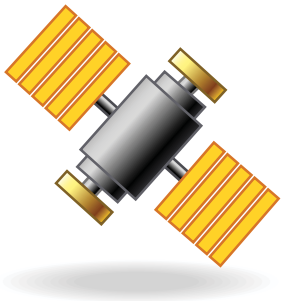

Monitoring particle pollution from space is still in its infancy.

cardiovascular mortality in a cohort of 2.1 million Canadian adults, and found similar results between satellite-derived estimates and ground-based measurements.[29] Studies of $PM_{2.5}$ acute health effects using satellite data have not been reported yet.

Prospectives for the Future

Monitoring particle pollution from space is still in its infancy. As the abilities of satellite aerosol sensors and CTMs improve with time, we will likely see both modeling approaches generate more accurate $PM_{2.5}$ estimates to significantly advance our understanding of the impact of ambient $PM_{2.5}$ on population health at urban to global scale. Nonetheless, a few challenges remain. Missing AOD values due to clouds and bright surfaces cause on average 40–50% data loss, which affects the prediction coverage of both approaches. Further research is needed to evaluate the impact that this non-random lack of data may have on satellite-based health effect studies, and to develop methods to fill the data gaps left by clouds. In addition, most current models were developed and evaluated in developed countries with low to moderate $PM_{2.5}$ levels. Model performance in heavily polluted regions including megacities in developing countries as well as rural areas with severe biomass burning activities must be carefully examined. **em**

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