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Open Access

AJAE

Vol. 14, No. 4, pp. 319-334, December 2020
doi: https://doi.org/10.5572/ajae.2020.14.4.319
ISSN (Online) 2287-1160, ISSN (Print) 1976-6912

Review Article

Advancing Exposure Assessment of $PM_{2.5}$ Using Satellite Remote Sensing: A Review

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Received: 31 August 2020
Revised: 28 October 2020
Accepted: 28 October 2020

ABSTRACT Epidemiological studies have reported the associations of adverse health outcomes with ambient particulate matter with aerodynamic diameter ≤2.5 μm ($PM_{2.5}$). While these studies have accumulated increasingly refined evidence on $PM_{2.5}$-health associations, the needs for more advanced $PM_{2.5}$ exposure models have also grown. For the last two decades, $PM_{2.5}$ estimation approaches using satellite remote sensing have been developed and advanced, taking advantage of quantitative aerosol data (e.g., aerosol optical depth; AOD), the development of satellite instruments and data retrieval algorithms, and the application of statistical and machine learning techniques. Subsequently, the satellite-based $PM_{2.5}$ concentrations have contributed to health effect studies by providing spatially resolved exposure estimates of ambient $PM_{2.5}$ and thus reducing exposure misclassification. This article summarizes previous development and recent advancement of satellite-based $PM_{2.5}$ exposure assessment in the context of satellite aerosol products and $PM_{2.5}$ estimation methodologies. Furthermore, this article deals with enhanced satellite capabilities of generating the exposure estimates of $PM_{2.5}$ composition and time-resolved $PM_{2.5}$. Finally, the future directions of satellite-based exposure assessment are discussed based on research needs and the satellite remote sensing technology of addressing them.

KEY WORDS AOD, Environmental epidemiology, Exposure assessment, $PM_{2.5}$, Public health, Satellite remote sensing

1. INTRODUCTION

Numerous epidemiological studies have reported the associations of ambient particulate matter with aerodynamic diameter ≤2.5 μm ($PM_{2.5}$) with adverse health outcomes (Lepeule *et al.*, 2012; Pope III *et al.*, 2002; Dockery *et al.*, 1993). The health effects of $PM_{2.5}$ include increased mortality and morbidity related to cardiovascular and respiratory functions, hospital admissions, neurological disorders, and adverse birth outcomes (Son *et al.*, 2017; Kioumourtzoglou *et al.*, 2016; Dominici *et al.*, 2006). Epidemiological studies investigate $PM_{2.5}$-health associations at two different temporal scales, short-term and long-term exposures and their associated acute and chronic health effects, respectively. In acute health effect studies, daily variation of $PM_{2.5}$ exposure is corresponded to that of health outcomes. For chronic health effect studies, on the other hand, average $PM_{2.5}$ exposures for months to years (typically annual) are related to health outcomes for the same periods.

Evidence on ambient $PM_{2.5}$ and health associations has led to establish or tighten ambient air quality standards for $PM_{2.5}$. The Harvard Six Cities study, which found an association between $PM_{2.5}$ air pollution and excess mortality (Dockery *et al.*, 1993), contributed to ambient $PM_{2.5}$ standards (65 μg/m^3 and 15 μg/m^3 for 24-hour and annual standards, respectively) by the U.S. Environmental Protection Agency (EPA) in 1997 (U.S. EPA, 2018). Since the mandate of $PM_{2.5}$ regulations, the $PM_{2.5}$ standards have been sequentially lowered to 35 μg/m^3 (24-hour) and 12 μg/m^3 (annual). Recent studies have shown that adverse health effects still exist below the current $PM_{2.5}$ standards (i.e., 'low-level' $PM_{2.5}$), motivating further discussions on the standards that can better protect public health (Yu *et al.*, 2020; Feng *et al.*, 2016; Shi *et al.*, 2016).

Epidemiological studies rely on the accuracy of exposure data (either measured or modeled) from $PM_{2.5}$ exposure assessment. When $PM_{2.5}$ exposure levels that are corresponded to subjects' health outcomes do not accurately represent their actual exposures (i.e., exposure misclassification), the $PM_{2.5}$-health associations would be obscured or biased (Zeger *et al.*, 2000). Traditionally, ground monitoring of $PM_{2.5}$ has been widely used to calculate daily or annual average $PM_{2.5}$ exposures. To alleviate the exposure misclassification due to sparsely distributed ground monitoring networks and thus generate more reliable exposure data, $PM_{2.5}$ modeling methodologies that exploit the capability of satellite remote sensing have been developed (Hoff and Christopher, 2009). These modeling approaches provide $PM_{2.5}$ exposure estimates in areas without ground monitoring in an effort to reflect actual $PM_{2.5}$ exposures more closely. Emerging evidence further suggests that the toxicity of $PM_{2.5}$ varies by its composition and sources, which may support regionally varying $PM_{2.5}$-health associations (Bell *et al.*, 2014; Son *et al.*, 2012; Franklin *et al.*, 2008).

This review article summarizes and discusses the following: (1) traditional $PM_{2.5}$ exposure assessment approaches using ground monitoring, (2) the development and advancement of satellite-based $PM_{2.5}$ exposure assessment, (3) satellite opportunities of $PM_{2.5}$ exposure assessment on $PM_{2.5}$ composition and time-resolved $PM_{2.5}$, and (4) future satellite-based exposure assessment to address research needs. Instead of discussing previous research in an exhaustive manner, this article emphasizes more widely recognized satellite products and exposure modeling approaches around the globe. Ultimately, this article is expected to contemplate lessons learned from previous research and motivate continuing efforts to elaborate the exposure assessment of $PM_{2.5}$.

2. $PM_{2.5}$ EXPOSURE ASSESSMENT USING GROUND $PM_{2.5}$ MEASUREMENTS

Traditionally, ground-based $PM_{2.5}$ measurements have been widely used as proxies of ambient $PM_{2.5}$ exposures for health effect studies in many parts of the world (Pascal *et al.*, 2014; Son *et al.*, 2012; Dominici *et al.*, 2006). Ground $PM_{2.5}$ concentrations are generally reported hourly or daily (24 hours). Hourly $PM_{2.5}$ is observed by continuous monitors such as Beta Attenuation Monitor (BAM; Met One Instruments, Inc., Grants Pass, OR, USA) and Tapered Element Oscillating Microbalance (TEOM; Thermo Scientific, Waltham, MA, USA), and daily $PM_{2.5}$ concentrations are measured by 24-hour integrated filter samples (e.g., Harvard Impactor) or calculated as the averages of 24 hourly concentrations observed from the continuous monitors. In developed countries, ground $PM_{2.5}$ concentrations are routinely monitored for a regulatory purpose. Ground $PM_{2.5}$ monitors can be also deployed to address specific research objectives that require denser air monitoring by time and space. However, in developing countries without any regulatory monitors, ground $PM_{2.5}$ monitors need to be established to obtain $PM_{2.5}$ exposure data.

The most acknowledged approach of ground-based exposure assessment is to correspond ambient $PM_{2.5}$ concentrations measured at a ground monitoring site, which is located in the closest proximity to subjects' residence or within the geographic boundaries of the residence (e.g., county, census tract, and province), to the subjects' health outcomes. However, as the distance from the residence to the monitor increases, the representativeness of the measured $PM_{2.5}$ concentrations for the subjects' exposures tends to be lower, as supported by lower site-to-site correlations of $PM_{2.5}$ concentrations with larger site-to-site distance (Bell *et al.*, 2011). The spatial heterogeneity of $PM_{2.5}$, evaluated by the correlations and differences of concentration levels,

Table 1. Satellite AOD products (Level 2) that are currently used to estimate ambient $PM_{2.5}$ concentrations.

Satellite	Instrument	Product*	Launch year	Target area	Spatial resolution	Temporal resolution
Polar-orbiting						
Terra	MODIS	DT	1999	Globe	10 and 3 km	Daily (10:30 am)
		DB	1999	Globe	10 km	Daily (10:30 am)
	MISR	–	1999	Globe	4.4 km	Every 9 days (10:30 am)
Aqua	MODIS	DT	2002	Globe	10 and 3 km	Daily (1:30 pm)
		DB	2002	Globe	10 km	Daily (1:30 pm)
Terra + Aqua	MODIS	MAIAC	–	Globe	1 km	Daily
Suomi NPP	VIIRS	EDR	2011	Globe	6 km	Daily (1:30 pm)
		IP	2011	Globe	750 m	Daily (1:30 pm)
Geostationary						
GOES-16 (East)	ABI	–	2016	U.S.	2 km	Every 15 minutes
GOES-17 (West)	ABI	–	2018	U.S.	2 km	Every 15 minutes
COMS	GOCI	–	2010	East Asia	6 km	Hourly
Himawari-8	AHI	–	2014	East Asia	5 km	Every 10 minutes

*DT: Dark Target, DB: Deep Blue, MAIAC: Multi-Angle Implementation of Atmospheric Correction, EDR: Environmental Data Record, IP: Intermediate Product

also varies by region, causing the ground-based exposure assessment to be susceptible to regionally varying exposure misclassification (Pinto *et al.*, 2004). Consequently, a specific constraint of distance between the locations of subjects and ground monitors is usually applied in epidemiological studies, and those subjects who do not meet the constraint are often excluded from the studies (Ebisu *et al.*, 2014).

Taking advantage of ground $PM_{2.5}$ measurements, interpolation techniques have been employed in order to assess subjects' exposures at the locations of their residence (Neupane *et al.*, 2010; Wu *et al.*, 2006; Jerrett *et al.*, 2005). A simple and common interpolation method is inverse distance weighting (IDW), and more sophisticated methods include kriging, natural neighbor, and spline among others (ESRI, 2017). The fundamental of the interpolation techniques is based on the tendency of more similar air pollution levels with closer spatial distance. With regards to $PM_{2.5}$, these techniques calculate a $PM_{2.5}$ concentration level that is unknown at a specific location by exploiting $PM_{2.5}$ concentration levels that are known at adjacent locations. The key advantage of using the interpolation techniques is that they only require ground $PM_{2.5}$ measurements without additional spatiotemporal information related to $PM_{2.5}$, which makes the approaches relatively easy to apply. However, the accuracy of the $PM_{2.5}$ concentration estimates depends on the distribution of ground $PM_{2.5}$ monitoring networks. As the term 'inter-polation' indicates, these techniques would be more appropriate when the location of interest with unknown $PM_{2.5}$ concentrations is surrounded by a larger number of locations with known $PM_{2.5}$ concentrations (i.e., in-between locations). Furthermore, the techniques may not be effective to estimate location-specific $PM_{2.5}$ concentrations that are higher than those at adjacent locations because the $PM_{2.5}$ concentration estimates are derived from spatial inter-dependency rather than direct observations from a specific location.

3. SATELLITE-BASED $PM_{2.5}$ EXPOSURE ASSESSMENT

3.1 Satellite Remote Sensing for $PM_{2.5}$

Since the launch of MODerate resolution Imaging Spectroradiometer (MODIS) on Aqua (1999) and Terra (2002) satellites by the National Aeronautics and Space Administration (NASA), satellite-based aerosol data have been increasingly used to infer ground-level $PM_{2.5}$ concentrations (Hoff and Christopher, 2009). Satellite instruments and algorithms retrieve data on aerosol optical depth (AOD; unitless), which is a measure of light extinction (i.e., scattering and absorption) by aerosols. Therefore, AOD reflects the abundance of $PM_{2.5}$ in the atmosphere, enabling AOD to be a reasonable proxy or predictor of $PM_{2.5}$. In general, AOD values reported at visible wavelengths (e.g., 550 nm) are used to derive $PM_{2.5}$ concentrations.

There are several key properties of satellite-retrieved AOD to determine the applicability of the aerosol data for ambient $PM_{2.5}$. First, the vertical profile of aerosols is unknown from most of satellite AOD products except for NASA's Cloud-Aerosol Lidar and Infrared Pathfinder Satellite Observation (CALIPSO). When aerosols are well-mixed within a planetary boundary layer height (i.e., near-surface level), satellite AOD tends to be closely related to ambient $PM_{2.5}$. On the contrary, satellite AOD may not well reflect ambient $PM_{2.5}$ with a large fraction of aerosols aloft above the mixing layer. Second, AOD and $PM_{2.5}$ are not the measures of indicating exactly same aerosol properties. $PM_{2.5}$ concentration measures dry mass per unit volume of air, while AOD represents aerosols that are affected by the level of relative humidity (i.e., hygroscopic property). With the same $PM_{2.5}$ level, AOD is likely to be higher in more humid atmospheric condition. Third, AOD does not represent specific size distribution of aerosols unlike $PM_{2.5}$ characterizing aerosols or PM with the aerodynamic diameter of 2.5 μm or less. Despite the potentially non-overlapping fraction of size distributions between AOD and $PM_{2.5}$, AOD is known to be sensitive to small-sized aerosols roughly with the diameters of 0.05–2.5 μm, which is similar to the size distribution of $PM_{2.5}$ (Liu *et al.*, 2007; Kahn *et al.*, 1998). Towards the end, the applicability of satellite AOD for ambient $PM_{2.5}$ concentrations depends on how well these factors, among others, are accounted for in the identification of $PM_{2.5}$-AOD relationships.

Table 1 shows a list of AOD products from multiple satellite instruments that are currently available. One of the most popular satellite AOD products is MODIS AOD data retrieved from NASA's Aqua and Terra satellites (Levy *et al.*, 2013). These two satellites were launched around the year 2000 (i.e., Terra in 1999 and Aqua in 2002), and MODIS instruments onboard Terra and Aqua have provided aerosol data for the last two decades. Under cloud-free conditions, these polar-orbiting satellites retrieve AOD data almost daily at a global scale at the spatial resolution of 3 km ('Dark Target' algorithm) and 10 km (both 'Dark Target' and 'Deep Blue' algorithms) (nominal resolution at nadir), crossing the equator approximately at 10:30 am (Terra) and 1:30 pm (Aqua) local sun time. Most recently in 2018, a new AOD data product, called Multi-Angle Implementation of Atmospheric Correction (MAIAC), was released to the public by NASA (Lyapustin *et al.*, 2018). The MAIAC AOD retrieval algorithm also utilizes observations from MODIS and provides AOD data at 1 km resolution, which enables the investigation of local-scale aerosol distributions to be viable. In addition to AOD retrievals from MODIS, Visible Infrared Imaging Radiometer Suite (VIIRS) onboard Suomi National Polar-orbiting Partnership (Suomi NPP), operated by the U.S. National Oceanic and Atmospheric Administration (NOAA), also generates spatiotemporal AOD data daily at the spatial resolution of 6 km (Environmental Data Record; EDR) and 750 m (Intermediate Product; IP) (Jackson *et al.*, 2013). The EDR AOD data are aggregated by 8 × 8 boxes of the IP AOD data.

Multi-angle Imaging SpectroRadiometer (MISR) onboard the Terra satellite has also retrieved AOD data by NASA's Jet Propulsion Laboratory (JPL) (Garay *et al.*, 2017; Diner *et al.*, 1998). The key advantage of MISR AOD over other AOD products is that the multi-angle feature of MISR enables aerosols to be monitored from 9 different cameras or angles, generating a range of quantitative aerosol properties such as fractional AOD components, representing the size, shape, and refractive index of aerosols, as well as total AOD. The spatial resolution of MISR AOD was originally 17.6 km and improved to 4.4 km in 2017. Due to MISR's rather coarse temporal resolution (every 9 days), day-to-day variability of $PM_{2.5}$ concentrations is not plausible to obtain from MISR AOD.

In addition to polar-orbiting satellites mentioned above, there are geostationary satellites that monitor aerosols at a high temporal resolution, such as Advanced Baseline Imager (ABI; Geostationary Operational Environmental Satellite (GOES-16 (East) and 17 (West); U.S. NOAA)) (Kondragunta *et al.*, 2020), Geostationary Ocean Color Imager (GOCI; Korea Institute of Ocean Science and Technology (KIOST)) (Choi *et al.*, 2018), and Advanced Himawari Imager (AHI; Japan Meteorological Agency (JMA)) (Yoshida *et al.*, 2018). The geostationary feature enables these satellites to provide AOD data hourly or sub-hourly during the daylight time and thus observe the diurnal variation of aerosols. However, the feature prevents them from covering the entire globe because they are only capable of looking down at a specific region of interest.

The selection of a specific AOD data product depends largely on the spatial and temporal resolutions and accuracy of AOD data to reasonably address the objectives of $PM_{2.5}$ exposure studies. In this regard, the pros and cons of the AOD products listed in Table 1 are relative and thus determined by these properties that meet specific research needs. When local or subject-specific $PM_{2.5}$ exposures are needed, AOD data at a finer spatial resolution (e.g., <10 km) would be more preferable. In case of examining $PM_{2.5}$ exposures at a global scale (e.g., global burden of disease (GBD)) (Brauer *et al.*, 2016), AOD data at a coarser resolution (e.g., ≥ 10 km) are still useful to estimate $PM_{2.5}$ exposures and correspond them to health outcomes at a country level. Because AOD data are not retrieved on days with cloud and snow cover, the satellite overpass frequency in combination with the proportion of cloud-free days determines the overall frequency of AOD retrievals. Hence, the AOD products with shorter retrieval frequency lead to $PM_{2.5}$ concentration estimates at a higher temporal resolution, which is more applicable to acute health effect studies. On the other hand, the accuracy of satellite-retrieved AOD data can be evaluated by comparing the data to AOD values obtained from the AErosol RObotic NETwork (AERONET) monitoring networks as ground-truth, which is a global network of ground-based remote sensing instruments (i.e., sun photometers) to retrieve the optical, microphysical, and radiative properties of aerosols (Holben *et al.*, 1998). A satellite AOD product that shows a better agreement with AERONET AOD (i.e., higher correlation, slope closer to 1, and intercept closer to 0 in a simple linear regression) demonstrates higher accuracy (Xiao *et al.*, 2016).

3.2 Early Development of Satellite-based $PM_{2.5}$ Concentrations

The simplest approach of estimating AOD-derived $PM_{2.5}$ concentrations is to employ a simple linear regression model (i.e., 1 independent variable or predictor in a model) and identify the relationship between AOD and $PM_{2.5}$ at the locations where both AOD values and measured $PM_{2.5}$ concentrations are available (Schaap *et al.*, 2009; Engel-Cox *et al.*, 2004; Wang and Christopher, 2003). This relationship (i.e., fitted model with an intercept and a slope estimated) is then used to estimate $PM_{2.5}$ from AOD at the locations where AOD data are available but ground $PM_{2.5}$ monitoring is not available. This initial methodology demonstrated space-dependent predictive power of AOD for $PM_{2.5}$, which was generally higher in areas with vegetation and homogeneous land and meteorology types (e.g., eastern U.S.) than in semi-arid and barren areas or areas with diverse terrains and meteorology (e.g., western U.S.) (Li *et al.*, 2015; Engel-Cox *et al.*, 2004). When satellite AOD values are corresponded to ground $PM_{2.5}$ measurements, two temporal scales of $PM_{2.5}$, i.e., $PM_{2.5}$ measured at a satellite overpass time and 24-hour average $PM_{2.5}$, are used in the objectives of performing the synoptic evaluation of AOD-to-$PM_{2.5}$ predictability and applying AOD-derived $PM_{2.5}$ for policy assessment and health effect studies, respectively.

Multiple linear regression models are employed to account for additional spatial and/or temporal factors (e.g., local meteorology and land use information) that influence $PM_{2.5}$ concentrations and thus $PM_{2.5}$-AOD relationships (also for PM_{10} depending on ground PM data availability) (Marsha and Larkin, 2019; Seo *et al.*, 2015; Gupta and Christopher, 2009b). The importance of adding the meteorological parameters into the model is attributed to atmospheric conditions that may affect $PM_{2.5}$ and AOD differently. For example, when planetary boundary layer height is lower (assuming the same area and amount of aerosols), the reduced air volume results in higher $PM_{2.5}$ concentrations but the column integrated AOD levels are likely to be the same. Adding data on planetary boundary layer height into the model would mitigate its disproportionate impacts on $PM_{2.5}$ and AOD to some extent. The meteorological parameters (e.g., relative humidity, temperature, wind speed, and planetary boundary layer height) can be obtained from ground weather stations (except for planetary boundary layer height) and global and regional meteorological modeling such as ERA5 (31 km resolution; European Centre for Medium-range Weather Forecasts (ECMWF)), Modern-Era Retrospective analysis for Research and Applications, Version 2 (MERRA-2, 0.5×0.625 degree; NASA), and North American Regional Reanalysis (NARR, 32 km resolution; NOAA) among others.

Land use parameters are incorporated with the model in order to explain the fine-scale $PM_{2.5}$ variability around ground $PM_{2.5}$ monitors as emission proxies. The 'land use' parameters are rather loosely defined and thus inclusive and generally used to represent any temporally invariant parameters, such as distance to roads, road density, population density, impervious areas, elevation, and distance to industrial complex. Some of the parameters vary by time in reality, but lack of frequent updates on the data leads them to be considered time-invariant in the model. On the other hand, the term 'fine-scale' is intended to represent smaller spatial scales than the spatial resolution of satellite AOD. For example, when a $PM_{2.5}$ monitor is located in close proximity to highways (i.e., traffic as a $PM_{2.5}$ emission source), measured $PM_{2.5}$ concentrations tend to be high, but satellite-based AOD may not well account for such near-source impacts depending on the relative scales of the spatial resolution of AOD data and the spatial heterogeneity of $PM_{2.5}$ around the highways. Consequently, the land use parameters are likely to be more beneficial with AOD data at a coarser spatial resolution.

In addition to the linear regression models described above, a statistical model called a generalized additive model (GAM) is utilized to allow non-linear relationships between $PM_{2.5}$ and independent variables (e.g., AOD, meteorology, and land use) (Strawa *et al.*, 2013; Liu *et al.*, 2009). When the non-linear or smooth function follows the actual relationships more closely than the linear function, replacing the linear function with the non-linear one would improve the $PM_{2.5}$ predictive power. However, the model predictability may also increase even when the non-linear function only follows pseudo relationships (i.e., data-driven wiggling patterns, causing model overfitting) regardless of the actual ones. To prevent the latter, those non-linear relationships need to be supported by scientific knowledge on atmospheric chemistry and physics. For instance, if the GAM displays a quadratic pattern between $PM_{2.5}$ and AOD, including both positive and inverse correlations, it is not likely to be an actual relationship that would be appropriate only with positive correlations.

Once linear or non-linear models are fitted, estimated $PM_{2.5}$ concentrations are validated by comparing them to measured $PM_{2.5}$ concentrations generally with the metrics of coefficient of determination (R^2), root mean squared error (RMSE), and mean absolute error (MAE). When the estimated and measured $PM_{2.5}$ concentrations are in a better agreement (i.e., higher R^2 and lower RMSE and MAE), the model estimates are considered to be more accurate. However, in this comparison, model overfitting may be caused because the same data are used for both model fitting and validation, likely overstating the model performance. To prevent the model performance from being overestimated, cross-validation (CV) techniques have been widely implemented by randomly splitting data into the subsets of the data (e.g., 10 equal sized subsets; 10-fold CV), fitting the model with all the subsets except for one, estimating $PM_{2.5}$ for the hold-out subset using the fitted model, and repeating the same process for each of the subsets (Liu *et al.*, 2009; Yanosky *et al.*, 2008). The equal sized subsets can be based on observations (i.e., same number of observations in each subset) and monitoring sites (e.g., all observations from the same number of sites in each subset). The observation-based CV is more advantageous than the site-based CV because the overall model performance is not influenced by the subset-specific number of observations, while the site-based CV is more appropriate in that $PM_{2.5}$ concentrations at a given site are estimated independently from those at other sites by non-overlapping predictors (e.g., land use parameters) (Lee, 2019). All the $PM_{2.5}$ concentration estimates from the CV analysis are compared to measured $PM_{2.5}$ concentrations to evaluate the overall model performance. In addition, the CV analysis can be performed separately by spatial and temporal portions of the model estimates (i.e., spatial and temporal CV R^2) (Kloog *et al.*, 2011). Instead of the CV analysis, the model estimates have been also validated by comparing them to measured $PM_{2.5}$ concentrations obtained from a monitoring network that is independent from the network used in the modeling processes (Knibbs *et al.*, 2018). This validation approach may be advantageous due to potential residual overfitting from the CV approach, but it is often not feasible to have an independent $PM_{2.5}$ monitoring network.

3.3 Advanced Approaches for Estimating Satellite-based $PM_{2.5}$ Exposures

The approach of using a mixed effects model to estimate AOD-derived $PM_{2.5}$ substantially improved the predictive power of AOD for $PM_{2.5}$ (CV R^2 between daily measured and estimated $PM_{2.5}=0.92$) (Lee *et al.*, 2011). Lee *et al.* (2011) showed that the mixed effects model outperformed the simple linear regression model (both models only with AOD), i.e., CV R^2 of 0.95 versus 0.51 (average of site-specific R^2), in the New England region of the U.S. (including Massachusetts, Connecticut, and Rhode Island). Since then, this modeling approach has been widely adopted by many researchers in the world, many of which incorporated additional spatiotemporal predictors into the model (Shtein *et al.*, 2020; de Hoogh *et al.*, 2018; Pereira *et al.*, 2017; Ma *et al.*, 2016; Just *et al.*, 2015; Xie *et al.*, 2015; Hu *et al.*, 2014; Kloog *et al.*, 2011).

The key feature of the mixed effects model is to allow day-to-day variability in the relationships between measured $PM_{2.5}$ concentrations and AOD values. The term 'mixed' represents a combination of 'fixed' and 'random' effects, which identifies an average relationship of $PM_{2.5}$ and AOD that is applied to the entire study period and the daily variations of the relationships (i.e., daily deviations from the average relationship; day-specific slopes and intercepts), respectively. On the contrary, the simple and multiple linear regression models and GAM only generate an average relationship between $PM_{2.5}$ and AOD for the entire period. As discussed above, the impacts of local meteorology and large-scale weather systems on the $PM_{2.5}$-AOD relationships tend to be diverse by day in a region. The mixed effects model implicitly accounts for such temporal parameters by allowing the $PM_{2.5}$-AOD relationships to vary on a daily basis, regardless of the feasibility of parameterizing and including each temporal parameter in the model. Moreover, the daily relationships of $PM_{2.5}$ and AOD, generated by the mixed effects model, are more robust than those derived from day-specific simple linear regression models, because the mixed effects model produces daily $PM_{2.5}$-AOD relationships by identifying the overall average relationship and then quantifying daily deviations from this average relationship. This is an important feature of the mixed effects model particularly due to the number of $PM_{2.5}$ and AOD pairs that varies by day. Furthermore, spatial variations in $PM_{2.5}$-AOD relationships were accounted for by adding region-specific relationships into the mixed effects model (Chudnovsky *et al.*, 2014) or by combining the model with a geographically weighted regression (GWR) model, which generates a continuous spatial surface of each parameter and subsequently identifies the local slopes of AOD for $PM_{2.5}$ with geographical weighting (Hu *et al.*, 2014).

The mixed effects modeling approach motivated the use of satellite-based $PM_{2.5}$ exposure estimates in acute and chronic health effect studies with low $PM_{2.5}$ modeling errors and subsequent gap-filling techniques exploiting those AOD-derived $PM_{2.5}$ (Son *et al.*, 2017; McGuinn *et al.*, 2016; Shi *et al.*, 2016; Hyder *et al.*, 2014). Previous studies developed statistical approaches to estimate $PM_{2.5}$ exposure levels for days without AOD data (largely due to cloud cover) by clustering days with similar $PM_{2.5}$ spatial patterns (Lee *et al.*, 2012) and by assuming season-specific $PM_{2.5}$ spatial patterns (Kloog *et al.*, 2011). These statistical approaches relied on AOD-derived $PM_{2.5}$ concentrations (i.e., days with AOD data) as a first step of estimating all the missing $PM_{2.5}$ concentrations, leading to no spatial and temporal gaps of $PM_{2.5}$ exposure estimates. These gap-filling approaches contributed to epidemiological studies that require both short-term and long-term $PM_{2.5}$ exposures such as subject-specific trimester $PM_{2.5}$ exposures and their birth outcomes (e.g., lower birth weight) (Hyder *et al.*, 2014) and hospital admissions (Kloog *et al.*, 2012). Finally, such modeling approaches facilitated health effect studies associated with $PM_{2.5}$ levels below current $PM_{2.5}$ standards (i.e., 'low-level' $PM_{2.5}$ and health) (Shi *et al.*, 2016). In the U.S., most of ground $PM_{2.5}$ monitors are located in highly populated urban or non-populated remote (i.e., forest; Interagency Monitoring of Protected Visual Environments (IMPROVE) network) areas, and satellite-based $PM_{2.5}$ exposure approaches enable epidemiological studies to include suburban and rural populations generally with 'low-level' $PM_{2.5}$ exposures.

A combination of chemical transport models (CTM) (e.g., GEOS-Chem, global 3-D simulations) and satellite AOD data has been also employed to estimate $PM_{2.5}$ exposures. Previous research simulated relationships between column AOD at a satellite overpass time and ground-level 24-hour average $PM_{2.5}$, which relied on the size, composition, and vertical and diurnal profiles of aerosols and relative humidity, and these relationships were used to calculate $PM_{2.5}$ as follows: [simulated (ground $PM_{2.5}$/column AOD) × satellite column AOD = estimated $PM_{2.5}$] (Liu *et al.*, 2004). This approach is different from statistical calibrations because the simulated conversion factors are not derived from empirical relationships between the observations of ground $PM_{2.5}$ and satellite AOD. Instead, the CTM simulations tracked the atmospheric processes of emissions and meteorology and thus quantified model-driven daily relationships of 24-hour average $PM_{2.5}$ and column AOD at a given satellite overpass time (van Donkelaar *et al.*, 2010). With respect to GEOS-Chem, daily conversion factors were calculated originally at the spatial resolution of $2° \times 2.5°$ (global), and nested simulations at the resolution of $0.5° \times 0.67°$ were conducted in selected regions such as North America, Europe, and East Asia (Hammer *et al.*, 2020). Despite the spatial resolution of estimated $PM_{2.5}$ generally following that of satellite AOD, the spatial resolution of the simulations for

Table 2. $PM_{2.5}$ estimation models developed by using satellite AOD data. The category is based on the primary focus of the models regardless of additional modeling approaches combined with. The applicability to epidemiological studies is assessed by the predictive power for $PM_{2.5}$.

Category	Predictor(s)	$PM_{2.5}$ estimation (references)	Applicability to epidemiological studies
Statistical model			
Simple linear regression	AOD	Wang and Christopher (2003), Engel-Cox *et al.* (2004)	Low
Multiple linear regression	AOD, meteorology, land use	Gupta and Christopher (2009b), Seo *et al.* (2015)	Low-Moderate
Generalized additive model	AOD, meteorology, land use	Liu *et al.* (2009), Strawa *et al.* (2013)	Moderate
Mixed effects model	AOD, meteorology, land use	Lee *et al.* (2011), Kloog *et al.* (2011)	High
CTM			
GEOS-Chem	AOD	Liu *et al.* (2004), van Donkelaar *et al.* (2010)	High
Machine learning			
Random forest	AOD, meteorology, land use	Hu *et al.* (2017), Park *et al.* (2019)	High
Neural network	AOD, meteorology, land use	Gupta and Christopher (2009a), Di *et al.* (2016)	High
(Extreme) Gradient boosting	AOD, meteorology, land use	Reid *et al.* (2015), Just *et al.* (2020)	High

the conversion factors may limit the ability of capturing local $PM_{2.5}$ gradients. As a recent improvement, the GWR modeling was further adopted to calibrate annual average $PM_{2.5}$ concentrations estimated from the conversion factors and satellite AOD for measured annual average $PM_{2.5}$ concentrations, while incorporating spatial parameters such as elevation and proximity to urban land surface, leading to CV R^2 of 0.81 (van Donkelaar *et al.*, 2016).

Due to the nature of global scale modeling, the approach of utilizing GEOS-Chem and satellite AOD (recently also with statistical calibration) has contributed to global burden of disease (GBD) studies, providing global long-term $PM_{2.5}$ exposure estimates (Brauer *et al.*, 2016). In addition, this modeling has been used to generate $PM_{2.5}$ exposure estimates for multi-country and nationwide health effect studies (Pinault *et al.*, 2016; Fleischer *et al.*, 2014). The approach of adopting GEOS-Chem and satellite AOD is useful particularly in developing countries where no ground monitoring exists and thus empirical models are not plausible. Nonetheless, ground $PM_{2.5}$ data are still necessary to further increase model predictability through statistical calibration (e.g., GWR) and validate model estimates.

3.4 Machine Learning for Satellite-based $PM_{2.5}$

As artificial intelligence (AI) has infiltrated into a wide range of industries, machine learning techniques can be also applied to the estimation of satellite-based $PM_{2.5}$ exposures and environmental health research in general (National Academies of Sciences, Engineering, and Medicine, 2019). Machine learning seeks to find the most accurate relationships between $PM_{2.5}$ and a number of predictors (i.e., 'training' similar to model fitting), while considering interactions between those predictors, and thus reach the best predictive power without explicitly specifying modeling assumptions (i.e., linear or non-linear) and structures (e.g., interactions between predictors). The training process tends to be more robust as more high-quality data are added into the dataset. Though the concept to apply machine learning for $PM_{2.5}$ or PM_{10} is nearly two decades old (Chaloulakou *et al.*, 2003; Pérez *et al.*, 2000), incorporating satellite AOD data with the machine learning frameworks is comparatively recent (Gupta and Christopher, 2009a). For the last few years, machine learning techniques have been implemented into numerous statistical and programming software packages (e.g., R packages), making the machine learning techniques more accessible to researchers.

A number of machine learning techniques such as neural network, random forest, and gradient boosting (or extreme gradient boosting) have been applied for $PM_{2.5}$ exposure estimates, taking advantage of simultaneous advancement of satellite remote sensing, machine learning tools, and computational infrastructure (Just *et al.*, 2020; Park *et al.*, 2019; Hu *et al.*, 2017; Di *et al.*, 2016; Reid *et al.*, 2015). These studies resulted in high predictive power for $PM_{2.5}$ in a range of CV R^2 roughly between 0.70 and 0.90. However, it is noted that the model performance is not directly comparable to each other due to different study periods and regions and selected predictors among others, and therefore it is challenging to conclude one machine learning approach performs better than the others. An ensemble modeling was further employed in an effort to generate more refined $PM_{2.5}$ estimations collectively from multiple CTMs, statistical (i.e., mixed effects model), and machine learning approaches and enhance the overall predictive power compared to each individual one (Shtein *et al.*, 2020). Furthermore, the machine learning approaches have imputed missing AOD or combined CTM-calibrated AOD to fill the spatial and temporal gaps of satellite-based $PM_{2.5}$ (Li *et al.*, 2020; Di *et al.*, 2016). Due to high accuracy of ambient $PM_{2.5}$ exposure estimates attributed to machine learning, those estimates have been employed in health effect studies (Wei *et al.*, 2020; Di *et al.*, 2017). A summary of the early development and recent advancement for AOD-derived $PM_{2.5}$ estimation approaches (i.e., simple linear regression through machine learning) is presented in Table 2.

Despite the capability of machine learning to process complex multi-dimensional data and thus enhance the predictive power, it is worthwhile to address scientific aspects of machine learning in the context of predictive accuracy versus 'black box'-like predictions. As discussed in the National Academies of Sciences, Engineering, and Medicine (NASEM) of the U.S., data quality, transparency, and reproducibility of machine learning need to be emphasized to further promote the use of machine learning for environmental health research (National Academies of Sciences, Engineering, and Medicine, 2019). Unlike statistical models, the processes of machine learning techniques do not yield the coefficients of each model predictor and their corresponding uncertainties. Hence, it is challenging to understand and evaluate scientific mechanisms and pathways that lead to the enhanced predictive power from machine learning. In this regard, statistical approaches described above are still crucial to delve into the relationships between each predictor and $PM_{2.5}$ exposure levels and prioritize input data resources for future improvement of $PM_{2.5}$ exposure models. Moreover, during the processes of machine learning, there are a number of details to be disclosed to reproduce outputs because they may cause substantial differences in the outputs (Peng, 2020).

4. $PM_{2.5}$ COMPOSITION FROM SATELLITE REMOTE SENSING

$PM_{2.5}$ composition is related to the emission sources of $PM_{2.5}$, which can lead to health effect studies associated with composition- or source-specific $PM_{2.5}$ exposures. For the last two decades, MISR onboard Terra satellite has provided aerosol optical properties including fractional AOD components, which have been used to estimate spatially resolved concentrations on $PM_{2.5}$ composition (i.e., sulfate, nitrate, organic carbon, elemental carbon, and dust) (Geng *et al.*, 2020; Meng *et al.*, 2018; Liu *et al.*, 2007). MISR-derived $PM_{2.5}$ composition concentrations may be more applicable for long-term average exposures than for daily variations of exposures due to lack of day-to-day retrievals (i.e., retrieval frequency of every 9 days in cloud-free conditions).

NASA JPL plans to launch a satellite instrument called the Multi-Angle Imager for Aerosols (MAIA) in 2022 (Diner *et al.*, 2018). As a successor of MISR, MAIA is also designed to retrieve data that can be used to estimate $PM_{2.5}$ composition. This satellite instrument specifically addresses health associations with $PM_{2.5}$ composition while collaborating with environmental epidemiologists from the planning stage of the mission. The MAIA mission selected 12 primary target areas (PTAs), 26 secondary target areas (STAs), and 3 calibration/validation target areas (CVTAs) across the world. To be eligible for the PTAs, a health cohort as well as ground $PM_{2.5}$ monitors (both total mass and composition) are required to calibrate satellite data for measured $PM_{2.5}$ composition concentrations and then apply the concentration estimates for epidemiological studies in each PTA. The MAIA instrument is designed to collect data from 3–4 revisits per week at the spatial resolution of 1 km. On the other hand, a health cohort is not required but there must be substantial data needs for $PM_{2.5}$ composition to be one of the STAs. Unlike previous satellite AOD products, the MAIA mission plans to release estimated $PM_{2.5}$ composition concentrations as well as total and fractional AOD data. A geostatistical regression model to estimate $PM_{2.5}$ composition would combine multiple data resources such as retrieved aerosol properties, land use parameters (e.g., population and urban density), and meteorology. When aerosol properties are not available from the satellite, the modeling process utilizes CTM-derived $PM_{2.5}$ composition instead of fractional AOD as a predictor. Ultimately, the MAIA mission plans to provide $PM_{2.5}$ composition data without any spatial and temporal gaps (along with PM_{10} and $PM_{2.5}$ mass concentrations). Up-to-date information on the launch and retrieval plans of MAIA can be found at the NASA JPL website (https://maia.jpl.nasa.gov/).

5. TIME-RESOLVED $PM_{2.5}$ FROM GEOSTATIONARY SATELLITES

Geostationary satellites such as GOES-16 and GOES-17 ABI (U.S.), GOCI (South Korea), and AHI (Japan) are able to broaden the current scope of $PM_{2.5}$ exposure assessment, exploiting hourly or sub-hourly aerosol data. Thus far, $PM_{2.5}$ exposures and health effect studies focus on their associations at a daily or coarser scale (i.e., short-term or long-term exposures and their corresponding acute or chronic health effects) largely due to limited sub-daily exposure and health data. The associations between short-term $PM_{2.5}$ exposures and acute health outcomes are generally investigated by adopting 24-hour average $PM_{2.5}$ concentrations. However, within the time window of 24 hours, $PM_{2.5}$ exposures tend to vary depending on subject-specific time-activity patterns, diurnal patterns of source emissions (e.g., higher traffic emissions during the rush hours), and meteorology (e.g., higher planetary boundary layer height in the middle of a day). Therefore, high $PM_{2.5}$ exposures at a certain time on a given day may play a critical role in triggering acute health effects that are identified in epidemiological studies examining daily exposure-response relationship.

Geostationary satellites are also suitable to assess $PM_{2.5}$ exposures from extreme air pollution events such as wildfires (Reid *et al.*, 2015). These satellites are capable of tracking the transport of wildfire plumes and determining the high impact zones of the plumes. Simultaneously, hourly or sub-hourly AOD levels reflect the fast-changing behaviors of the plumes depending on local meteorology and terrains. The information on time-resolved AOD and subsequent $PM_{2.5}$ concentrations can be also used to alert the public of unhealthy $PM_{2.5}$ exposure levels. Recent studies reported the application of real-time individual health monitoring systems for air pollution and health effect studies (Pepper *et al.*, 2020; Su *et al.*, 2017), and the development of such health monitoring tools may facilitate access to health data at high spatial and temporal resolutions. Unlike spatially and temporally aggregated health data, these types of health data have a potential to be corresponded to time-resolved $PM_{2.5}$ exposures derived from the geostationary satellites.

6. FUTURE DIRECTIONS

For the last two decades, satellite remote sensing has advanced $PM_{2.5}$ exposure assessment by providing spatially resolved ambient $PM_{2.5}$ concentrations as a proxy of personal exposures to $PM_{2.5}$ (origin of outdoors). Satellite-based $PM_{2.5}$ exposure assessment is able to reasonably address local (e.g., within-urban and within-rural), regional (e.g., urban and rural areas), national (e.g., state-to-state or province-to-province), and global (e.g., country-to-country) $PM_{2.5}$ air pollution and its associated health outcomes. Despite the uncertainties inherently included in such exposure model estimates, satellite remote sensing obtains $PM_{2.5}$ exposure information directly from locations of interest, filling the spatial gaps of ground monitoring and potentially reducing $PM_{2.5}$ exposure misclassification attributed to the spatial misalignment between ground monitoring and subjects' locations. Furthermore, satellite observations have capabilities to broaden the scopes of $PM_{2.5}$ exposure assessment into $PM_{2.5}$ composition and time-resolved $PM_{2.5}$.

Hybrid approaches across multiple satellite products, multi-tiered data resources, and modeling methodologies are expected to continue to enhance the overall capability of satellite observations for $PM_{2.5}$ exposure assessment. A number of polar-orbiting and geostationary satellites are currently in the orbit and generate aerosol products with their product-specific advantages and limitations. In the coming years, next-generation satellite instruments will be added to the orbit (e.g., NASA JPL's MAIA), motivating even more synergistic approaches. Because people breathe air as a whole not by a specific air pollutant, a multi-pollutant approach dealing with other air pollutants as well as $PM_{2.5}$ (i.e., a mixture of air pollutants) (Dominici *et al.*, 2010) would benefit from satellite data on nitrogen dioxide (NO_2), sulfur dioxide (SO_2), and carbon monoxide (CO), among others, obtained from Ozone Monitoring Instrument (OMI, Aura) and TROPOspheric Monitoring Instrument (TROPOMI, Sentinel-5 Precursor) and in the near future, Geostationary Environment Monitoring Spectrometer (GEMS, South Korea), Tropospheric Emissions: Monitoring Pollution (TEMPO, U.S.), and Sentinel-4 (Europe). Other ground-based monitoring technologies such as low-cost sensors and mobile monitoring are also available (Bi *et al.*, 2020; Apte *et al.*, 2017), which may be further combined with satellite-based approaches. In addition, the ensemble models of multiple statistical and machine learning methodologies would be more commonly used as 'big data' and more sophisticated modeling approaches and user-friendly data processing platforms are anticipated in the future. Finally, the data assimilation of current and future AOD data resources in combination with CTMs is likely to improve air quality forecasting, which is crucial for extreme air pollution events (Pang *et al.*, 2018; Liu *et al.*, 2011).

Size-resolved PM exposure assessment such as coarse PM ($PM_{10-2.5}$) would help refine the health associations of PM, leading to size-relevant PM health risks (Ebisu *et al.*, 2016). The size, composition, and sources of PM are inter-connected (e.g., smaller PM from combustion than from mechanical processes) (Masri *et al.*, 2015), and size-relevant PM and health associations may reflect size-specific toxicity due to size itself and/or its relationships with composition and sources. As satellite remote sensing provides data on the size of PM (e.g., size-fractioned AOD from MISR) (Franklin *et al.*, 2017), satellite-based research on $PM_{10-2.5}$ as well as $PM_{2.5}$ is expected to contribute to size-relevant PM epidemiology in a spatially resolved manner. The comprehensive framework of PM exposure assessment that can be enhanced by satellite remote sensing is described in Fig. 1.

A global COVID-19 pandemic brings more attention to $PM_{2.5}$ air pollution due to a recent study that reported higher COVID-19 death rates in areas with higher historical long-term $PM_{2.5}$ concentrations (Wu *et al.*, 2020). Previous studies have also reported that the exposure to ambient $PM_{2.5}$ was higher in socially more vulnerable populations (Hajat *et al.*, 2013; Miranda *et al.*, 2011). Hence, social vulnerability that is related to $PM_{2.5}$ exposures needs to be understood in the context of social determinants of health disparities. Socially vulnerable populations are unevenly distributed within urban and rural areas, and a larger proportion of those populations are located in closer proximity to $PM_{2.5}$ emission sources such as highways (Lee and Park, 2020). To reflect such distributions of $PM_{2.5}$ and social vulnerability, the satellite observations are critical, leading to comprehensive $PM_{2.5}$ exposure research that represents all populations and the investigation of potential $PM_{2.5}$ health risks that are linked with social vulnerability (Lee, 2019). Finally, satellite-based $PM_{2.5}$ exposure assessment in association with social vulnerability would contribute to policy interventions that mitigate the disparities of $PM_{2.5}$ exposures and adverse health outcomes.

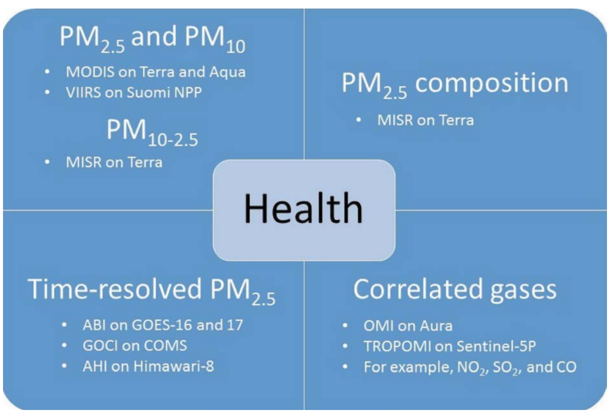

Fig. 1. Comprehensive framework of PM exposure assessment that can be addressed by satellite remote sensing.

DISCLAIMER

This review article was not written as part of state-funded research activities. Therefore, the statements and conclusions in this article are those of the author and do not represent the official views of the California Air Resources Board.

CONFLICTS OF INTEREST

No actual or potential conflict of interest.

REFERENCES

Apte, J.S., Messier, K.P., Gani, S., Brauer, M., Kirchstetter, T.W., Lunden, M.M., Marshall, J.D., Portier, C.J., Vermeulen, R.C.H., Hamburg, S.P. (2017) High-Resolution Air Pollution Mapping with Google Street View Cars: Exploiting Big Data. Environmental Science & Technology, 51, 6999–7008. https://doi.org/10.1021/acs.est.7b00891

Bell, M.L., Ebisu, K., Leaderer, B.P., Gent, J.F., Lee, H.J., Koutrakis, P., Wang, Y., Dominici, F., Peng, R.D. (2014) Associations of $PM_{2.5}$ Constituents and Sources with Hospital Admissions: Analysis of Four Counties in Connecticut and Massachusetts (USA) for Persons $\geq$65 Years of Age. Environmental Health Perspectives, 122, 138–144. https://doi.org/10.1289/ehp.1306656

Bell, M.L., Ebisu, K., Peng, R.D. (2011) Community-level spatial heterogeneity of chemical constituent levels of fine particulates and implications for epidemiological research. Journal of Exposure Science & Environmental Epidemiology, 21, 372-384. https://doi.org/10.1038/jes.2010.24

Bi, J., Wildani, A., Chang, H.H., Liu, Y. (2020) Incorporating Low-Cost Sensor Measurements into High-Resolution $PM_{2.5}$ Modeling at a Large Spatial Scale. Environmental Science & Technology, 54, 2152-2162. https://doi.org/10.1021/acs.est.9b06046

Brauer, M., Freedman, G., Frostad, J., van Donkelaar, A., Martin, R.V., Dentener, F., Dingenen, R.V., Estep, K., Amini, H., Apte, J.S., Balakrishnan, K., Barregard, L., Broday, D., Feigin, V., Ghosh, S., Hopke, P.K., Knibbs, L.D., Kokubo, Y., Liu, Y., Ma, S., Morawska, L., Sangrador, J.L.T., Shaddick, G., Anderson, H.R., Vos, T., Forouzanfar, M.H., Burnett, R.T., Cohen, A. (2016) Ambient Air Pollution Exposure Estimation for the Global Burden of Disease 2013. Environmental Science & Technology, 50, 79-88. https://doi.org/10.1021/acs.est.5b03709

Chaloulakou, A., Grivas, G., Spyrellis, N. (2003) Neural Network and Multiple Regression Models for PM_{10} Prediction in Athens: A Comparative Assessment. Journal of the Air & Waste Management Association, 53, 1183-1190. https://doi.org/10.1080/10473289.2003.10466276

Choi, M., Kim, J., Lee, J., Kim, M., Park, Y.J., Holben, B., Eck, T.F., Li, Z., Song, C.H. (2018) GOCI Yonsei aerosol retrieval version 2 products: an improved algorithm and error analysis with uncertainty estimation from 5-year validation over East Asia. Atmospheric Measurement Techniques, 11, 385-408. https://doi.org/10.5194/amt-11-385-2018

Chudnovsky, A.A., Koutrakis, P., Kloog, I., Melly, S., Nordio, F., Lyapustin, A., Wang, Y., Schwartz, J. (2014) Fine particulate matter predictions using high resolution Aerosol Optical Depth (AOD) retrievals. Atmospheric Environment, 89, 189-198. https://doi.org/10.1016/j.atmosenv.2014.02.019

de Hoogh, K., Héritier, H., Stafoggia, M., Künzli, N., Kloog, I. (2018) Modelling daily $PM_{2.5}$ concentrations at high spatiotemporal resolution across Switzerland. Environmental Pollution, 233, 1147-1154. https://doi.org/10.1016/j.envpol.2017.10.025

Di, Q., Kloog, I., Koutrakis, P., Lyapustin, A., Wang, Y., Schwartz, J. (2016) Assessing $PM_{2.5}$ Exposures with High Spatiotemporal Resolution across the Continental United States. Environmental Science & Technology, 50, 4712-4721. https://doi.org/10.1021/acs.est.5b06121.

Di, Q., Wang, Y., Zanobetti, A., Wang, Y., Koutrakis, P., Choirat, C., Dominici, F., Schwartz, J.D. (2017) Air Pollution and Mortality in the Medicare Population. New England Journal of Medicine, 376, 2513-2522. https://doi.org/10.1056/NEJMoa1702747

Diner, D., Boland, S., Brauer, M., Bruegge, C., Burke, K., Chipman, R., Di Girolamo, L., Garay, M., Hasheminassab, S., Hyer, E., Jerrett, M., Jovanovic, V., Kalashnikova, O., Liu, Y., Lyapustin, A., Martin, R., Nastan, A., Ostro, B., Ritz, B., Schwartz, J., Wang, J., Xu, F. (2018) Advances in multiangle satellite remote sensing of speciated airborne particulate matter and association with adverse health effects: from MISR to MAIA. Journal of Applied Remote Sensing, 12, 042603. https://doi.org/10.1117/1.JRS.12.042603

Diner, D.J., Beckert, J.C., Reilly, T.H., Bruegge, C.J., Conel, J.E., Kahn, R.A., Martonchik, J.V., Ackerman, T.P., Davies, R., Gerstl, S.A.W., Gordon, H.R., Muller, J., Myneni, R.B., Sellers, P.J., Pinty, B., Verstraete, M.M. (1998) Multi-angle Imaging SpectroRadiometer (MISR) instrument description and experiment overview. IEEE Transactions on Geoscience and Remote Sensing, 36, 1072-1087. https://doi.org/10.1109/36.700992

Dockery, D.W., Pope, C.A., Xu, X., Spengler, J.D., Ware, J.H., Fay, M.E., Ferris, B.G., Speizer, F.E. (1993) An Association between Air Pollution and Mortality in Six U.S. Cities. New England Journal of Medicine, 329, 1753-1759. https://doi.org/10.1056/nejm199312093292401

Dominici, F., Peng, R.D., Barr, C.D., Bell, M.L. (2010) Protecting Human Health From Air Pollution: Shifting From a Single-pollutant to a Multipollutant Approach. Epidemiology, 21, 187-194. https://doi.org/10.1097/EDE.0b013e3181cc86e8

Dominici, F., Peng, R.D., Bell, M.L., Pham, L., McDermott, A., Zeger, S.L., Samet, J.M. (2006) Fine Particulate Air Pollution and Hospital Admission for Cardiovascular and Respiratory Diseases. Journal of the American Medical Association, 295, 1127-1134. https://doi.org/10.1001/jama.295.10.1127

Ebisu, K., Belanger, K., Bell, M.L. (2014) Association between airborne $PM_{2.5}$ chemical constituents and birth weight-implication of buffer exposure assignment. Environmental Research Letters, 9, 084007. https://doi.org/10.1088/1748-9326/9/8/084007

Ebisu, K., Berman, J.D., Bell, M.L. (2016) Exposure to coarse particulate matter during gestation and birth weight in the U.S.. Environment International, 94, 519-524. https://doi.org/10.1016/j.envint.2016.06.011

Engel-Cox, J.A., Holloman, C.H., Coutant, B.W., Hoff, R.M. (2004) Qualitative and quantitative evaluation of MODIS satellite sensor data for regional and urban scale air quality. Atmospheric Environment, 38, 2495-2509. https://doi.org/10.1016/j.atmosenv.2004.01.039

Environmental Systems Research Institute (ESRI) (2017) Comparing interpolation methods. https://desktop.arcgis.com/en/arcmap/10.5/tools/spatial-analyst-toolbox/comparing-interpolation-methods.htm (10 June 2020).

Feng, S., Gao, D., Liao, F., Zhou, F., Wang, X. (2016) The health effects of ambient $PM_{2.5}$ and potential mechanisms. Ecotoxicology and Environmental Safety, 128, 67-74. https://doi.org/10.1016/j.ecoenv.2016.01.030

Fleischer, N.L., Merialdi, M., van Donkelaar, A., Vadillo-Ortega, F., Martin, R.V., Betran, A.P., Souza, J.P. (2014) Outdoor Air Pollution, Preterm Birth, and Low Birth Weight: Analysis of the World Health Organization Global Survey on Maternal and Perinatal Health. Environmental Health Perspectives, 122, 425-430. https://doi.org/10.1289/ehp.1306837

Franklin, M., Kalashnikova, O.V., Garay, M.J. (2017) Size-resolved particulate matter concentrations derived from 4.4 km-resolution size-fractionated Multi-angle Imaging SpectroRadiometer (MISR) aerosol optical depth over Southern California. Remote Sensing of Environment, 196, 312-323. https://doi.org/10.1016/j.rse.2017.05.002

Franklin, M., Koutrakis, P., Schwartz, J. (2008) The Role of Particle Composition on the Association Between $PM_{2.5}$ and

Mortality. Epidemiology, 19, 680–689. https://doi.org/10.1097/EDE.0b013e3181812bb7
Garay, M.J., Kalashnikova, O.V., Bull, M.A. (2017) Development and assessment of a higher-spatial-resolution (4.4 km) MISR aerosol optical depth product using AERONET-DRAGON data. Atmospheric Chemistry and Physics, 17, 5095–5106. https://doi.org/10.5194/acp-17-5095-2017
Geng, G., Meng, X., He, K., Liu, Y. (2020) Random forest models for $PM_{2.5}$ speciation concentrations using MISR fractional AODs. Environmental Research Letters, 15, 034056. https://doi.org/10.1088/1748-9326/ab76df
Gupta, P., Christopher, S.A. (2009a) Particulate matter air quality assessment using integrated surface, satellite, and meteorological products: 2. A neural network approach. Journal of Geophysical Research: Atmospheres, 114, D20205. https://doi.org/10.1029/2008jd011497
Gupta, P., Christopher, S.A. (2009b) Particulate matter air quality assessment using integrated surface, satellite, and meteorological products: Multiple regression approach. Journal of Geophysical Research: Atmospheres, 114, D14205. https://doi.org/10.1029/2008jd011496
Hajat, A., Diez-Roux, A.V., Adar, S.D., Auchincloss, A.H., Lovasi, G.S., O'Neill, M.S., Sheppard, L., Kaufman, J.D. (2013) Air Pollution and Individual and Neighborhood Socioeconomic Status: Evidence from the Multi-Ethnic Study of Atherosclerosis (MESA). Environmental Health Perspectives, 121, 1325–1333. https://doi.org/10.1289/ehp.1206337
Hammer, M.S., van Donkelaar, A., Li, C., Lyapustin, A., Sayer, A.M., Hsu, N.C., Levy, R.C., Garay, M.J., Kalashnikova, O.V., Kahn, R.A., Brauer, M., Apte, J.S., Henze, D.K., Zhang, L., Zhang, Q., Ford, B., Pierce, J.R., Martin, R.V. (2020) Global Estimates and Long-Term Trends of Fine Particulate Matter Concentrations (1998–2018). Environmental Science & Technology, 54, 7879–7890. https://doi.org/10.1021/acs.est.0c01764
Hoff, R.M., Christopher, S.A. (2009) Remote Sensing of Particulate Pollution from Space: Have We Reached the Promised Land?. Journal of the Air & Waste Management Association, 59, 645–675. https://doi.org/10.3155/1047-3289.59.6.645
Holben, B.N., Eck, T.F., Slutsker, I., Tanré, D., Buis, J.P., Setzer, A., Vermote, E., Reagan, J.A., Kaufman, Y.J., Nakajima, T., Lavenu, F., Jankowiak, I., Smirnov, A. (1998) AERONET-A Federated Instrument Network and Data Archive for Aerosol Characterization. Remote Sensing of Environment, 66, 1–16. https://doi.org/10.1016/S0034-4257(98)00031-5
Hu, X., Belle, J.H., Meng, X., Wildani, A., Waller, L.A., Strickland, M.J., Liu, Y. (2017) Estimating $PM_{2.5}$ Concentrations in the Conterminous United States Using the Random Forest Approach. Environmental Science & Technology, 51, 6936–6944. https://doi.org/10.1021/acs.est.7b01210
Hu, X., Waller, L.A., Lyapustin, A., Wang, Y., Al-Hamdan, M.Z., Crosson, W.L., Estes, M.G., Estes, S.M., Quattrochi, D.A., Puttaswamy, S.J., Liu, Y. (2014) Estimating ground-level $PM_{2.5}$ concentrations in the Southeastern United States using MAIAC AOD retrievals and a two-stage model. Remote Sensing of Environment, 140, 220–232. https://doi.org/10.1016/j.rse.2013.08.032
Hyder, A., Lee, H.J., Ebisu, K., Koutrakis, P., Belanger, K., Bell, M.L. (2014) $PM_{2.5}$ Exposure and Birth Outcomes: Use of Satellite- and Monitor-Based Data. Epidemiology, 25, 58–67. https://doi.org/10.1097/ede.0000000000000027
Jackson, J.M., Liu, H., Laszlo, I., Kondragunta, S., Remer, L.A., Huang, J., Huang, H.-C. (2013) Suomi-NPP VIIRS aerosol algorithms and data products. Journal of Geophysical Research: Atmospheres, 118, 12673–12689. https://doi.org/10.1002/2013jd020449
Jerrett, M., Burnett, R.T., Ma, R., Pope, C.A.I., Krewski, D., Newbold, K.B., Thurston, G., Shi, Y., Finkelstein, N., Calle, E.E., Thun, M.J. (2005) Spatial Analysis of Air Pollution and Mortality in Los Angeles. Epidemiology, 16, 727–736. https://doi.org/10.1097/01.ede.0000181630.15826.7d
Just, A.C., Arfer, K.B., Rush, J., Dorman, M., Shtein, A., Lyapustin, A., Kloog, I. (2020) Advancing methodologies for applying machine learning and evaluating spatiotemporal models of fine particulate matter ($PM_{2.5}$) using satellite data over large regions. Atmospheric Environment, 239, 117649. https://doi.org/10.1016/j.atmosenv.2020.117649
Just, A.C., Wright, R.O., Schwartz, J., Coull, B.A., Baccarelli, A.A., Tellez-Rojo, M.M., Moody, E., Wang, Y., Lyapustin, A., Kloog, I. (2015) Using High-Resolution Satellite Aerosol Optical Depth To Estimate Daily $PM_{2.5}$ Geographical Distribution in Mexico City. Environmental Science & Technology, 49, 8576–8584. https://doi.org/10.1021/acs.est.5b00859
Kahn, R., Banerjee, P., McDonald, D., Diner, D.J. (1998) Sensitivity of multiangle imaging to aerosol optical depth and to pure-particle size distribution and composition over ocean. Journal of Geophysical Research: Atmospheres, 103, 32195–32213. https://doi.org/10.1029/98jd01752
Kioumourtzoglou, M.-A., Schwartz, J.D., Weisskopf, M.G., Melly, S.J., Wang, Y., Dominici, F., Zanobetti, A. (2016) Long-term $PM_{2.5}$ Exposure and Neurological Hospital Admissions in the Northeastern United States. Environmental Health Perspectives, 124, 23–29. https://doi.org/10.1289/ehp.1408973
Kloog, I., Coull, B.A., Zanobetti, A., Koutrakis, P., Schwartz, J.D. (2012) Acute and Chronic Effects of Particles on Hospital Admissions in New-England. PLOS ONE, 7, e34664. https://doi.org/10.1371/journal.pone.0034664
Kloog, I., Koutrakis, P., Coull, B.A., Lee, H.J., Schwartz, J. (2011) Assessing temporally and spatially resolved $PM_{2.5}$ exposures for epidemiological studies using satellite aerosol optical depth measurements. Atmospheric Environment, 45, 6267–6275. https://doi.org/10.1016/j.atmosenv.2011.08.066
Knibbs, L.D., van Donkelaar, A., Martin, R.V., Bechle, M.J., Brauer, M., Cohen, D.D., Cowie, C.T., Dirgawati, M., Guo, Y., Hanigan, I.C., Johnston, F.H., Marks, G.B., Marshall, J.D., Pereira, G., Jalaludin, B., Heyworth, J.S., Morgan, G.G., Barnett, A.G. (2018) Satellite-Based Land-Use Regression for Continental-Scale Long-Term Ambient $PM_{2.5}$ Exposure Assessment in Australia. Environmental Science & Technology, 52, 12445–12455. https://doi.org/10.1021/acs.est.8b02328
Kondragunta, S., Laszlo, I., Zhang, H., Ciren, P., Huff, A., 2020. Chapter 17 - Air Quality Applications of ABI Aerosol Prod-

ucts from the GOES-R Series, Goodman, S.J., Schmit, T.J., Daniels, J., Redmon, R.J. (Eds.), The GOES-R Series. Elsevier, pp. 203–217. https://doi.org/10.1016/B978-0-12-814327-8.00017-2

Lee, H.J. (2019) Benefits of High Resolution $PM_{2.5}$ Prediction using Satellite MAIAC AOD and Land Use Regression for Exposure Assessment: California Examples. Environmental Science & Technology, 53, 12774–12783. https://doi.org/10.1021/acs.est.9b03799

Lee, H.J., Coull, B.A., Bell, M.L., Koutrakis, P. (2012) Use of satellite-based aerosol optical depth and spatial clustering to predict ambient $PM_{2.5}$ concentrations. Environmental Research, 118, 8–15. https://doi.org/10.1016/j.envres.2012.06.011

Lee, H.J., Liu, Y., Coull, B.A., Schwartz, J., Koutrakis, P. (2011) A novel calibration approach of MODIS AOD data to predict $PM_{2.5}$ concentrations. Atmospheric Chemistry and Physics, 11, 7991–8002. https://doi.org/10.5194/acp-11-7991-2011

Lee, H.J., Park, H.-Y. (2020) Prioritizing the control of emission sources to mitigate $PM_{2.5}$ disparity in California. Atmospheric Environment, 224, 117316. https://doi.org/10.1016/j.atmosenv.2020.117316

Lepeule, J., Laden, F., Dockery, D., Schwartz, J. (2012) Chronic Exposure to Fine Particles and Mortality: An Extended Follow-up of the Harvard Six Cities Study from 1974 to 2009. Environmental Health Perspectives, 120, 965–970. https://doi.org/10.1289/ehp.1104660

Levy, R.C., Mattoo, S., Munchak, L.A., Remer, L.A., Sayer, A.M., Patadia, F., Hsu, N.C. (2013) The Collection 6 MODIS aerosol products over land and ocean. Atmospheric Measurement Techniques, 6, 2989–3034. https://doi.org/10.5194/amt-6-2989-2013

Li, J., Carlson, B.E., Lacis, A.A. (2015) How well do satellite AOD observations represent the spatial and temporal variability of $PM_{2.5}$ concentration for the United States?. Atmospheric Environment, 102, 260–273. https://doi.org/10.1016/j.atmosenv.2014.12.010

Li, L., Franklin, M., Girguis, M., Lurmann, F., Wu, J., Pavlovic, N., Breton, C., Gilliland, F., Habre, R. (2020) Spatiotemporal imputation of MAIAC AOD using deep learning with downscaling. Remote Sensing of Environment, 237, 111584. https://doi.org/10.1016/j.rse.2019.111584

Liu, Y., Koutrakis, P., Kahn, R. (2007) Estimating Fine Particulate Matter Component Concentrations and Size Distributions Using Satellite-Retrieved Fractional Aerosol Optical Depth: Part 1-Method Development. Journal of the Air & Waste Management Association, 57, 1351–1359. https://doi.org/10.3155/1047-3289.57.11.1351

Liu, Y., Paciorek, C.J., Koutrakis, P. (2009) Estimating Regional Spatial and Temporal Variability of $PM_{2.5}$ Concentrations Using Satellite Data, Meteorology, and Land Use Information. Environmental Health Perspectives, 117, 886–892. https://doi.org/10.1289/ehp.0800123

Liu, Y., Park, R.J., Jacob, D.J., Li, Q., Kilaru, V., Sarnat, J.A. (2004) Mapping annual mean ground-level $PM_{2.5}$ concentrations using Multiangle Imaging Spectroradiometer aerosol optical thickness over the contiguous United States. Journal of Geophysical Research: Atmospheres, 109, D22206. https://doi.org/10.1029/2004jd005025

Liu, Z., Liu, Q., Lin, H.-C., Schwartz, C.S., Lee, Y.-H., Wang, T. (2011) Three-dimensional variational assimilation of MODIS aerosol optical depth: Implementation and application to a dust storm over East Asia. Journal of Geophysical Research: Atmospheres, 116, D23206. https://doi.org/10.1029/2011JD016159

Lyapustin, A., Wang, Y., Korkin, S., Huang, D. (2018) MODIS Collection 6 MAIAC algorithm. Atmospheric Measurement Techniques, 11, 5741–5765. https://doi.org/10.5194/amt-11-5741-2018

Ma, Z., Hu, X., Sayer, A.M., Levy, R., Zhang, Q., Xue, Y., Tong, S., Bi, J., Huang, L., Liu, Y. (2016) Satellite-Based Spatiotemporal Trends in $PM_{2.5}$ Concentrations: China, 2004-2013. Environmental Health Perspectives, 124, 184–192. https://doi.org/10.1289/ehp.1409481

Marsha, A., Larkin, N.K. (2019) A statistical model for predicting $PM_{2.5}$ for the western United States. Journal of the Air & Waste Management Association, 69, 1215–1229. https://doi.org/10.1080/10962247.2019.1640808

Masri, S., Kang, C.-M., Koutrakis, P. (2015) Composition and sources of fine and coarse particles collected during 2002–2010 in Boston, MA. Journal of the Air & Waste Management Association, 65, 287–297. https://doi.org/10.1080/10962247.2014.982307

McGuinn, L.A., Ward-Caviness, C.K., Neas, L.M., Schneider, A., Diaz-Sanchez, D., Cascio, W.E., Kraus, W.E., Hauser, E., Dowdy, E., Haynes, C., Chudnovsky, A., Koutrakis, P., Devlin, R.B. (2016) Association between satellite-based estimates of long-term $PM_{2.5}$ exposure and coronary artery disease. Environmental Research, 145, 9–17. https://doi.org/10.1016/j.envres.2015.10.026

Meng, X., Garay, M.J., Diner, D.J., Kalashnikova, O.V., Xu, J., Liu, Y. (2018) Estimating $PM_{2.5}$ speciation concentrations using prototype 4.4 km-resolution MISR aerosol properties over Southern California. Atmospheric Environment, 181, 70–81. https://doi.org/10.1016/j.atmosenv.2018.03.019

Miranda, M.L., Edwards, S.E., Keating, M.H., Paul, C.J. (2011) Making the Environmental Justice Grade: The Relative Burden of Air Pollution Exposure in the United States. International Journal of Environmental Research and Public Health, 8, 1755–1771. https://doi.org/10.3390/ijerph8061755

National Academies of Sciences, Engineering, and Medicine (2019) Leveraging Artificial Intelligence and Machine Learning to Advance Environmental Health Research and Decisions: Proceedings of a Workshop-in Brief. The National Academies Press, Washington, DC. https://doi.org/10.17226/25520

Neupane, B., Jerrett, M., Burnett, R.T., Marrie, T., Arain, A., Loeb, M. (2010) Long-Term Exposure to Ambient Air Pollution and Risk of Hospitalization with Community-acquired Pneumonia in Older Adults. American Journal of Respiratory and Critical Care Medicine, 181, 47–53. https://doi.org/10.1164/rccm.200901-0160OC

Pang, J., Liu, Z., Wang, X., Bresch, J., Ban, J., Chen, D., Kim, J. (2018) Assimilating AOD retrievals from GOCI and VIIRS to forecast surface $PM_{2.5}$ episodes over Eastern China.

Atmospheric Environment, 179, 288–304. https://doi.org/10.1016/j.atmosenv.2018.02.011

Park, S., Shin, M., Im, J., Song, C.K., Choi, M., Kim, J., Lee, S., Park, R., Kim, J., Lee, D.W., Kim, S.K. (2019) Estimation of ground-level particulate matter concentrations through the synergistic use of satellite observations and process-based models over South Korea. Atmospheric Chemistry and Physics, 19, 1097–1113. https://doi.org/10.5194/acp-19-1097-2019

Pascal, M., Falq, G., Wagner, V., Chatignoux, E., Corso, M., Blanchard, M., Host, S., Pascal, L., Larrieu, S. (2014) Short-term impacts of particulate matter (PM_{10}, $PM_{10-2.5}$, $PM_{2.5}$) on mortality in nine French cities. Atmospheric Environment, 95, 175–184. https://doi.org/10.1016/j.atmosenv.2014.06.030

Peng, R.D. (2020) Opportunities for Artificial Intelligence and Machine Learning in Environmental Health. https://www.healtheffects.org/annual-conference (15 August 2020).

Pepper, J.R., Barrett, M.A., Su, J.G., Merchant, R., Henderson, K., Van Sickle, D., Balmes, J.R. (2020) Geospatial-temporal analysis of the impact of ozone on asthma rescue inhaler use. Environment International, 136, 105331. https://doi.org/10.1016/j.envint.2019.105331

Pereira, G., Lee, H.J., Bell, M., Regan, A., Malacova, E., Mullins, B., Knibbs, L.D. (2017) Development of a model for particulate matter pollution in Australia with implications for other satellite-based models. Environmental Research, 159, 9–15. https://doi.org/10.1016/j.envres.2017.07.044

Pérez, P., Trier, A., Reyes, J. (2000) Prediction of $PM_{2.5}$ concentrations several hours in advance using neural networks in Santiago, Chile. Atmospheric Environment, 34, 1189–1196. https://doi.org/10.1016/S1352-2310(99)00316-7

Pinault, L., Tjepkema, M., Crouse, D.L., Weichenthal, S., van Donkelaar, A., Martin, R.V., Brauer, M., Chen, H., Burnett, R.T. (2016) Risk estimates of mortality attributed to low concentrations of ambient fine particulate matter in the Canadian community health survey cohort. Environmental Health, 15, 18. https://doi.org/10.1186/s12940-016-0111-6

Pinto, J.P., Lefohn, A.S., Shadwick, D.S. (2004) Spatial Variability of $PM_{2.5}$ in Urban Areas in the United States. Journal of the Air & Waste Management Association, 54, 440–449. https://doi.org/10.1080/10473289.2004.10470919

Pope III, C.A., Burnett, R.T., Thun, M.J., Calle, E.E., Krewski, D., Ito, K., Thurston, G.D. (2002) Lung Cancer, Cardiopulmonary Mortality, and Long-term Exposure to Fine Particulate Air Pollution. Journal of the American Medical Association, 287, 1132–1141. https://doi.org/10.1001/jama.287.9.1132

Reid, C.E., Jerrett, M., Petersen, M.L., Pfister, G.G., Morefield, P.E., Tager, I.B., Raffuse, S.M., Balmes, J.R. (2015) Spatiotemporal Prediction of Fine Particulate Matter During the 2008 Northern California Wildfires Using Machine Learning. Environmental Science & Technology, 49, 3887–3896. https://doi.org/10.1021/es505846r

Schaap, M., Apituley, A., Timmermans, R.M.A., Koelemeijer, R.B.A., de Leeuw, G. (2009) Exploring the relation between aerosol optical depth and $PM_{2.5}$ at Cabauw, the Netherlands. Atmospheric Chemistry and Physics, 9, 909–925. https://doi.org/10.5194/acp-9-909-2009

Seo, S., Kim, J., Lee, H., Jeong, U., Kim, W., Holben, B.N., Kim, S.W., Song, C.H., Lim, J.H. (2015) Estimation of PM_{10} concentrations over Seoul using multiple empirical models with AERONET and MODIS data collected during the DRAGON-Asia campaign. Atmospheric Chemistry and Physics, 15, 319–334. https://doi.org/10.5194/acp-15-319-2015

Shi, L., Zanobetti, A., Kloog, I., Coull, B.A., Koutrakis, P., Melly, S.J., Schwartz, J.D. (2016) Low-Concentration $PM_{2.5}$ and Mortality: Estimating Acute and Chronic Effects in a Population-Based Study. Environmental Health Perspectives, 124, 46–52. https://doi.org/10.1289/ehp.1409111

Shtein, A., Kloog, I., Schwartz, J., Silibello, C., Michelozzi, P., Gariazzo, C., Viegi, G., Forastiere, F., Karnieli, A., Just, A.C., Stafoggia, M. (2020) Estimating Daily $PM_{2.5}$ and PM_{10} over Italy Using an Ensemble Model. Environmental Science & Technology, 54, 120–128. https://doi.org/10.1021/acs.est.9b04279

Son, J.-Y., Lee, H.J., Koutrakis, P., Bell, M.L. (2017) Pregnancy and Lifetime Exposure to Fine Particulate Matter and Infant Mortality in Massachusetts, 2001–2007. American Journal of Epidemiology, 186, 1268–1276. https://doi.org/10.1093/aje/kwx015

Son, J.-Y., Lee, J.-T., Kim, K.-H., Jung, K., Bell, M.L. (2012) Characterization of Fine Particulate Matter and Associations between Particulate Chemical Constituents and Mortality in Seoul, Korea. Environmental Health Perspectives, 120, 872–878. https://doi.org/10.1289/ehp.1104316

Strawa, A.W., Chatfield, R.B., Legg, M., Scarnato, B., Esswein, R. (2013) Improving retrievals of regional fine particulate matter concentrations from Moderate Resolution Imaging Spectroradiometer (MODIS) and Ozone Monitoring Instrument (OMI) multisatellite observations. Journal of the Air & Waste Management Association, 63, 1434–1446. https://doi.org/10.1080/10962247.2013.822838

Su, J.G., Barrett, M.A., Henderson, K., Humblet, O., Smith, T., Sublett, J.W., Nesbitt, L., Hogg, C., Sickle, D.V., Sublett, J.L. (2017) Feasibility of Deploying Inhaler Sensors to Identify the Impacts of Environmental Triggers and Built Environment Factors on Asthma Short-Acting Bronchodilator Use. Environmental Health Perspectives, 125, 254–261. https://doi.org/10.1289/EHP266

U.S. EPA (2018) Table of Historical Particulate Matter (PM) National Ambient Air Quality Standards (NAAQS). https://www.epa.gov/pm-pollution/table-historical-particulate-matter-pm-national-ambient-air-quality-standards-naaqs (15 July 2020).

van Donkelaar, A., Martin, R.V., Brauer, M., Hsu, N.C., Kahn, R.A., Levy, R.C., Lyapustin, A., Sayer, A.M., Winker, D.M. (2016) Global Estimates of Fine Particulate Matter using a Combined Geophysical-Statistical Method with Information from Satellites, Models, and Monitors. Environmental Science & Technology, 50, 3762–3772. https://doi.org/10.1021/acs.est.5b05833

van Donkelaar, A., Martin, R.V., Brauer, M., Kahn, R., Levy, R., Verduzco, C., Villeneuve, P.J. (2010) Global Estimates of Ambient Fine Particulate Matter Concentrations from Satellite-Based Aerosol Optical Depth: Development and Application. Environmental Health Perspectives, 118, 847–855. https://doi.org/10.1289/ehp.0901623

Wang, J., Christopher, S.A. (2003) Intercomparison between satellite-derived aerosol optical thickness and $PM_{2.5}$ mass: Implications for air quality studies. Geophysical Research Letters, 30, 2095. https://doi.org/10.1029/2003gl018174

Wei, Y., Wang, Y., Wu, X., Di, Q., Shi, L., Koutrakis, P., Zanobetti, A., Dominici, F., Schwartz, J.D. (2020) Causal Effects of Air Pollution on Mortality in Massachusetts. American Journal of Epidemiology, 189, 1316–1323. https://doi.org/10.1093/aje/kwaa098

Wu, J., Winer, A.M., Delfino, R.J. (2006) Exposure assessment of particulate matter air pollution before, during, and after the 2003 Southern California wildfires. Atmospheric Environment, 40, 3333–3348. https://doi.org/10.1016/j.atmosenv.2006.01.056

Wu, X., Nethery, R.C., Sabath, M.B., Braun, D., Dominici, F. (2020) Air pollution and COVID-19 mortality in the United States: Strengths and limitations of an ecological regression analysis. Science Advances, 6, eabd4049. https://doi.org/10.1126/sciadv.abd4049

Xiao, Q., Zhang, H., Choi, M., Li, S., Kondragunta, S., Kim, J., Holben, B., Levy, R.C., Liu, Y. (2016) Evaluation of VIIRS, GOCI, and MODIS Collection 6 AOD retrievals against ground sunphotometer observations over East Asia. Atmospheric Chemistry and Physics, 16, 1255–1269. https://doi.org/10.5194/acp-16-1255-2016

Xie, Y., Wang, Y., Zhang, K., Dong, W., Lv, B., Bai, Y. (2015) Daily Estimation of Ground-Level $PM_{2.5}$ Concentrations over Beijing Using 3 km Resolution MODIS AOD. Environmental Science & Technology, 49, 12280-12288. https://doi.org/10.1021/acs.est.5b01413

Yanosky, J.D., Paciorek, C.J., Schwartz, J., Laden, F., Puett, R., Suh, H.H. (2008) Spatio-temporal modeling of chronic PM_{10} exposure for the Nurses' Health Study. Atmospheric Environment, 42, 4047-4062. https://doi.org/10.1016/j.atmosenv.2008.01.044

Yoshida, M., Kikuchi, M., Nagao, T.M., Murakami, H., Nomaki, T., Higurashi, A. (2018) Common Retrieval of Aerosol Properties for Imaging Satellite Sensors. Journal of the Meteorological Society of Japan, 96B, 193–209. https://doi.org/10.2151/jmsj.2018-039

Yu, W., Guo, Y., Shi, L., Li, S. (2020) The association between long-term exposure to low-level $PM_{2.5}$ and mortality in the state of Queensland, Australia: A modelling study with the difference-in-differences approach. PLoS Medicine, 17, e1003141. https://doi.org/10.1371/journal.pmed.1003141

Zeger, S.L., Thomas, D., Dominici, F., Samet, J.M., Schwartz, J., Dockery, D., Cohen, A. (2000) Exposure measurement error in time-series studies of air pollution: concepts and consequences. Environmental Health Perspectives, 108, 419–426. https://doi.org/10.1289/ehp.00108419