Published in final edited form as:

J Air Waste Manag Assoc. 2019 December ; 69(12): 1391–1414. doi:10.1080/10962247.2019.1668498.

Methods, availability, and applications of $PM_{2.5}$ exposure estimates derived from ground measurements, satellite, and atmospheric models

Minghui Diao[a,*], **Tracey Holloway**[b], **Seohyun Choi**[b], **Susan M. O'Neill**[c], **Mohammad Z. Al-Hamdan**[d], **Aaron van Donkelaar**[e], **Randall V. Martin**[e,f,g], **Xiaomeng Jin**[h], **Arlene M. Fiore**[h], **Daven K. Henze**[i], **Forrest Lacey**[i,j], **Patrick L. Kinney**[k], **Frank Freedman**[a], **Narasimhan K. Larkin**[c], **Yufei Zou**[l], **James T. Kelly**[m], **Ambarish Vaidyanathan**[n]

[a]San Jose State University, Department of Meteorology and Climate Science, One Washington Square, San Jose, California, USA, 95192-0104

[b]University of Wisconsin-Madison, Nelson Institute Center for Sustainability and the Global Environment (SAGE) and Department of Atmospheric and Oceanic Sciences, 201A Enzyme Institute, 1710 University Ave., Madison, Wisconsin, USA, 53726

[c]United States Department of Agriculture Forest Service, Pacific Northwest Research Station, Seattle, WA, USA, 98103-8600

[d]Universities Space Research Association, NASA Marshall Space Flight Center, National Space Science and Technology Center, 320 Sparkman Dr., Huntsville, Alabama, USA, 35805

[e]Dalhousie University, Department of Physics and Atmospheric Science, 6299 South St, Halifax, Nova Scotia, Canada, B3H 4R2

[f]Smithsonian Astrophysical Observatory, Harvard-Smithsonian Center for Astrophysics, Cambridge, MA, USA, 02138

[g]Department of Energy, Environmental & Chemical Engineering, Washington University in St. Louis, St. Louis, Missouri, USA, 63130

[h]Columbia University, Department of Earth and Environmental Sciences and Lamont-Doherty Earth Observatory, 61 Route 9W, Palisades, New York, USA, 10964

[i]University of Colorado, Mechanical Engineering Department, 1111 Engineering Drive UCB 427, Boulder, CO, USA, 80309

[j]National Center for Atmospheric Research, Atmospheric Chemistry Observations and Modeling, 3450 Mitchell Ln, Boulder, CO, USA, 80301

[k]Boston University School of Public Health, Department of Environmental Health, 715 Albany Street, Talbot 4W, Boston, Massachusetts, USA, 02118

[l]University of Washington, School of Environmental and Forest Sciences, Anderson Hall, Seattle, WA, USA, 98195

[*]**Corresponding author:** Minghui Diao, Assistant Professor, Department of Meteorology and Climate Science, San Jose State University, Minghui.diao@sjsu.edu.

[m]Office of Air Quality Planning & Standards, U.S. Environmental Protection Agency, Research Triangle Park, NC, USA 27711

[n]Asthma and Community Health Branch, Centers for Disease Control and Prevention, 1600 Clifton Road, Mail Stop E-19, Atlanta, Georgia, USA, 30333.

Abstract

Fine particulate matter ($PM_{2.5}$) is a well-established risk factor for public health. To support both health risk assessment and epidemiological studies, data are needed on spatial and temporal patterns of $PM_{2.5}$ exposures. This review article surveys publicly available exposure datasets for surface $PM_{2.5}$ mass concentrations over the contiguous U.S., summarizes their applications and limitations, and provides suggestions on future research needs. The complex landscape of satellite instruments, model capabilities, monitor networks, and data synthesis methods offers opportunities for research development, but would benefit from guidance for new users. Guidance is provided to access publicly available $PM_{2.5}$ datasets, to explain and compare different approaches for dataset generation, and to identify sources of uncertainties associated with various types of datasets. Three main sources used to create $PM_{2.5}$ exposure data are: ground-based measurements (especially regulatory monitoring), satellite retrievals (especially aerosol optical depth, AOD), and atmospheric chemistry models. We find inconsistencies among several publicly available $PM_{2.5}$ estimates, highlighting uncertainties in the exposure datasets that are often overlooked in health effects analyses. Major differences among $PM_{2.5}$ estimates emerge from the choice of data (ground-based, satellite, and/or model), the spatiotemporal resolutions, and the algorithms used to fuse data sources.

Keywords

$PM_{2.5}$ exposure estimate; satellite AOD; ground monitors; model simulations; wildfire; air quality; public health

Introduction

Particulate matter (PM) is a well-established health risk factor, with impacts on human morbidity and mortality through cardiovascular (Brook et al., 2010) and respiratory diseases (Dominici et al., 2006; Wu et al., 2018; Ni et al., 2015), lung cancer and cardiopulmonary mortality (Pope III et al., 2002; Hoek et al., 2013), premature births (Malley et al., 2017) and other types of diseases (Tian et al., 2017; Lin et al., 2017). Particulate matter is a combination of solid particles and liquid droplets that are suspended in the air, and are typically classified by size as PM_{10}, particles that are 10 micrometers or smaller in aerodynamic diameter, and $PM_{2.5}$, particles that are 2.5 micrometers or smaller in aerodynamic diameter (EPA, 2018a). Of these, $PM_{2.5}$ poses a greater risk to human health, as it can penetrate further into the lungs and typically contains more toxic components than larger particles (Wilson and Suh, 1997). $PM_{2.5}$ also has a lower rate of gravitational settling, so it can travel long distances in the atmosphere and affect regions far from the emission source, if not removed by precipitation (Ouyang et al., 2015). In this study, we focus on

$PM_{2.5}$, although many of the methodological issues relevant to $PM_{2.5}$ also relate to PM_{10} and, in some cases, gas-phase pollutants as well.

Epidemiological and clinical studies have confirmed an association between both acute and long-term exposures to $PM_{2.5}$ and adverse cardiorespiratory health effects (Dominici et al., 2006; Peters et al., 2001; Pope and Dockery, 2006). $PM_{2.5}$ was ranked the sixth highest risk factor in the Global Burden of Disease estimates of global premature mortality in 2016, and it was also ranked first among all outdoor air pollutants (State of Global Air, 2018). In recent years, $PM_{2.5}$ data have been used for (1) epidemiological studies, which quantify relationships between $PM_{2.5}$ exposure and adverse health outcomes, (2) health benefit assessments, which combine pollution concentrations, population data, baseline rates of adverse health outcomes, and concentration-response functions from previously conducted epidemiologic studies, to estimate the $PM_{2.5}$-related health burden, and (3) tools to support public health interventions from episodic events such as wildfires and dust storms, including inexpensive, rapid-response health impact assessment tools (Anenberg et al., 2016).

In an annual trend analysis, the global and regional emissions of PM species are often found to be correlated with energy consumption (Klimont et al., 2017). In the U.S., anthropogenic emissions of $PM_{2.5}$ from various sources (i.e., stationary, mobile and fire sources) are documented in the national emissions inventory report by EPA (EPA, 2017). One unique example of fine particulate matter emission on a short time scale is wildfires. In the U.S., 69% of the population were exposed to $PM_{2.5}$ above 0.2 $\mu g/m^3$ due to seasonal wildfire events (Munoz-Alpizar et al., 2017). Inhalation of $PM_{2.5}$ from wildfire smoke has been associated with increased cardiopulmonary and cerebrovascular hospital admissions and emergency department visits in affected communities (Gan et al. 2017; Rappold et al., 2011; Wettstein et al., 2018), and studies show that wildfire smoke may be a triggering factor for acute csoronary events (Haikerwal et al., 2015). Detailed evaluation has also been done to investigate the mutagenicity and lung toxicity of particulate matter from different fuel types and burning phases of fires (Kim et al., 2018). More research progress on wildfire health impact studies can be found in recent reviews (Stefanidou et al., 2008; Henderson and Johnston, 2012; Reid et al., 2016; Liu et al., 2015).

In the U.S., compliance with the annual and daily (24-hour) average $PM_{2.5}$ from the Environmental Protection Agency (EPA) National Ambient Air Quality Standards (NAAQS) is solely determined by ground-based regulatory monitoring data. While $PM_{2.5}$ is monitored in most large U.S. cities, many parts of the U.S. have no ground-based measurements of $PM_{2.5}$ to assess health impacts (EPA, 2018b). Even in areas with multiple ground-based $PM_{2.5}$ instruments, there are challenges in extrapolating point-based measurements to characterize regional air quality. Local emissions and variations in geography can lead to a high level of spatial heterogeneity in measurements, such that two monitors near each other may reflect very different $PM_{2.5}$ levels. There is no consensus approach generalizing point-based estimates to ascertain prevailing population-level $PM_{2.5}$ exposure over a community or neighborhood. Furthermore, temporal variability, especially during episodic high exposure events such as wildfires, that leads to short-term health effects is an important public health concern (Gan et al., 2017).

Satellite retrievals and atmospheric models have been used to complement ground-based monitoring data, and to estimate ambient $PM_{2.5}$ levels in areas with no direct measurements. Satellite instruments can provide information on atmospheric or land use characteristics associated with air pollution levels but cannot measure near-surface $PM_{2.5}$ in a manner directly comparable to measurements. Most satellite aerosol products are integrated values from the Earth's surface to the top of the atmosphere. As a result, these instruments cannot directly provide near-surface $PM_{2.5}$ but instead retrieve the "aerosol optical depth" (AOD), which is defined as the light extinction due to particles in the entire column of air.

The relationship between near-surface $PM_{2.5}$ and satellite data AOD is spatially and temporally heterogeneous. Models that estimate the AOD-$PM_{2.5}$ relationship may be categorized as geoscience-based or statistical: geoscience-based methods use atmospheric models to solve equations of physical and chemical processes, which is a forward approach to simulate the near-surface $PM_{2.5}$ and AOD; statistical models extrapolate data based on empirical associations. In the case of $PM_{2.5}$, both geoscience-based and statistical methods have evolved as valuable approaches to estimate ground-level concentrations in areas lacking direct measurements. Geoscience-based models, also referred to as chemical transport models, are used extensively to inform air quality management programs in addition to characterizing AOD-$PM_{2.5}$ relationships. Here we review estimates of spatially continuous $PM_{2.5}$ data for the contiguous United States, and how these estimates were constructed using one or more of these three data sources: measurements, satellite data, and models. Several previous articles have reviewed technical methods to generate surface $PM_{2.5}$ data, including over regions with few monitors (Zhang et al., 2018), from remote sensing techniques (Hoff and Christopher, 2009; Chu et al., 2016), and data assimilation methods (Lynch et al., 2016). Here we focus instead on existing data sources that are publicly available and easily accessible by the health and air quality communities. The complex landscape of satellite instruments, model capabilities, monitor networks, and data synthesis methods offers opportunities at the spatial and temporal scales of relevance to address questions of interest. Thus, a main goal of this work is to presents an array of options for estimating near-surface $PM_{2.5}$ using publicly available datasets, and provide guidance to new users to access and assess these data. We extend a previous review by van Donkelaar et al. (2010) that addressed the relationship between AOD and measured $PM_{2.5}$ (Engel-Cox et al., 2004; J. Wang and Christopher, 2003), meteorological factors (Gupta et al., 2006; Koelemeijer et al., 2006; Liu et al., 2005), and the synthesis of multiple data sources on a global basis. Specifically, we provide an overview of methods to develop spatially continuous $PM_{2.5}$ estimates (Section 2); compare existing $PM_{2.5}$ estimates for the contiguous U.S. that have been used or cited in past studies, discuss applications of satellite-derived data for wildfires and the global burden of disease (Section 3); and finally summarize the current status and future directions for $PM_{2.5}$ estimates (Section 4).

Overview of Four Basic Types of $PM_{2.5}$ Datasets

We describe the generation and applications of four types of $PM_{2.5}$ datasets: 1) ground-based monitor data; 2) ground-based monitor data merged with satellite data; 3) ground-based monitor data merged with model data; 4) ground-based monitor data merged with satellite and model data. Indirect ground-based observations such as visibility (Li et al.,

EPA Author Manuscript

EPA Author Manuscript

2016) are not discussed here, nor are short-term research field campaigns that offer extensive data for individual regions over a period of days to months.

2.1 Ground-based monitoring data

Over the U.S., extensive networks of ground-based instruments operated by state, local and Tribal agencies continuously monitor $PM_{2.5}$. Measurements from these monitors are archived by the U.S. EPA (https://www.epa.gov/outdoor-air-quality-data) and are freely available, to support assessment at annual, daily, and often hourly time scales. Spatially continuous real-time maps can be viewed on the EPA AirNow website. These data are used by cities, counties, states and the EPA to determine compliance with the NAAQS, by atmospheric modelers for model evaluation, and by health researchers as input to epidemiological studies and risk assessments. $PM_{2.5}$ data from ground monitors can be used to study correlations with adverse health impacts using area-wide averaging or nearest-monitor exposure assignments, such as a previous study of correlation with daily mortality in six U.S. cities (Laden et al., 2000) and a study of the American Cancer Society that links particulate air pollution and mortality (Krewski et al., 2009). Alternatively, various interpolation methods can be employed to create spatially continuous data fields, such as Land Use Regression (LUR) modeling, ordinary kriging interpolation, and inverse distant weighted interpolation (Menut et al., 2013; Zhang et al., 2018). Relative to other sources, monitor data are often treated as the “gold standard,” but the spatial coverage of pollution monitors limits the application of these data for health assessment, and can subsequently introduce errors where point-based monitors are used to assess health over a wider domain (Zeger et al., 2000). In certain cases such as Keller and Peng (2019), spatial prediction models showed better accuracy than monitoring averaging for exposure assignment, although both methods have limitations.

Before 1999, all $PM_{2.5}$ measurements were collected using a filter-based method at 24-hour or longer time averages. Since 1999, the EPA $PM_{2.5}$ monitoring system has been providing daily, continuous mass measurements reported as hourly averages. Most $PM_{2.5}$ monitors either use the Federal Reference Method (FRM) or the Federal Equivalent Methods (FEMs) (Noble et al., 2010). Many other types of ground-based monitors exist beyond FRM and FEMs with varying levels of measurement accuracy, and comparisons have been made of the measurements among various instruments (Turpin et al., 1994; Hering and Cass, 1999; Allen et al., 1997; Chow et al., 2008 and references therein). The aerosol water content in $PM_{2.5}$ is operationally defined, with dependence on both the instrument and network. For example, filters collected by the U.S. EPA are equilibrated at 30%–40% (within ±5%) of relative humidity (RH) (Chow and Watson, 1998), while the European standard is 50% RH (European Committee for Standardization, 1998). Some instruments use heaters to evaporate aerosol water that also evaporates semi-volatile material. These different practices complicate comparison across ground monitors and networks.

Related networks include the EPA Chemical Speciation Monitoring Network (CSN, launched in 2000) and the Interagency Monitoring of Protected Visual Environments (IMPROVE) program (Malm et al., 1994), which operates a network of ~170 PM monitors primarily in U.S. Wilderness Areas and National Parks. Both networks provide 24-hour average $PM_{2.5}$ concentrations, measured every three to six days, where a chemical analysis is performed to identify the elemental carbon, organic carbon, ammonium-sulfate, ammonium-nitrate, sea salt, soil, and other trace constituents. The field and laboratory approach is similar for both networks, despite differences in sampling and chemical analysis (Solomon et al., 2014).

In addition to the EPA monitors (typically located in highly populated areas) and IMPROVE monitors (located in rural background areas), temporary $PM_{2.5}$ monitors are deployed as a part of the Wildland Fire Air Quality Response Program (WFAQRP, https://wildlandfiresmoke.net/) during periods of wide-scale smoke impacts from wildfire. The temporary monitors are a mix of Environmental Beta Attenuation Monitors (EBAMs) and E-Samplers manufactured by Met One, Inc. The monitors are not FRM monitors, but can provide real-time information about $PM_{2.5}$ exposure. They are often deployed in remote, small towns where smoke impacts are heavy and other monitors do not exist. A web-based monitoring data tool merges data from these monitors with $PM_{2.5}$ data from the EPA AirNowTech system, providing time-series graphs and data that are downloadable (see https://tools.airfire.org/monitoring).

2.2 Data merged from ground monitors and satellites

Satellite remote sensing of AOD generally offers more spatially extensive observational information than ground-based $PM_{2.5}$ measurements (except for regions with perpetual issues due to cloud cover, snow cover, bright surface, viewing geometry, etc.). In this way, satellite data directly complement point-based estimates of $PM_{2.5}$ from monitors. Several studies have developed linear regression models for estimating $PM_{2.5}$ concentrations from remotely-sensed AOD (Wang and Christopher, 2003; Gupta et al., 2006; Gupta and Christopher, 2009; Al-Hamdan et al., 2009; Zhang et al., 2009), and others have added meteorological parameters to develop multiple regression models or generalized additive models for surface $PM_{2.5}$ (Liu et al., 2007; Liu et al., 2005; Paciorek et al., 2008; Hu et al., 2014a; Ma et al., 2014). Statistical approaches often incorporate ancillary data, such as meteorological fields, land use, and road density, to derive surface $PM_{2.5}$ based on merged data from ground monitors and satellites. The relationships between satellite retrievals of AOD and $PM_{2.5}$ measured by ground monitors are often evaluated by correlation coefficients (R), which are based on estimates and observed values in cross-validation exercise. The R values have been reported to be sensitive to various geographical locations and show large spatial and temporal variabilities (Hu, et al., 2014a; Kloog et al., 2014; Paciorek et al., 2008; Hu et al. 2014b). In fact, the performance of the derived $PM_{2.5}$ in the statistical approach relies on the availability, quality and the consistency of both ground-based observations and ancillary data, so past studies have typically been limited to a single county or a group of U.S. states, e.g., in the southeast (Hu et al., 2014a; Hu et al., 2014b; Lee et al., 2016; Bi et al., 2019) and northeast (Kloog et al., 2014) U.S.

Despite the value of satellite data in providing spatial coverage to complement information from point-based monitors, satellite data have several limitations. In terms of temporal coverage, the polar-orbiting satellites (e.g., MODIS, MISR, VIIRS, etc.) can only sample AOD at overpass times, once or twice a day or fewer (e.g., not over cloudy or snow-covered regions). Only a few studies have used instruments aboard geostationary satellites to examine surface $PM_{2.5}$, such as the Geostationary Operational Environmental Satellite (GOES) aerosol/smoke product (GASP) (Liu et al., 2009) and the Korean Geostationary Ocean Color Imager (GOCI) AOD product (Xiao et al., 2016; Lennartson et al., 2018; Xu et al., 2015). There are also issues with missing data in satellite observations, particularly over clouds (Kokhanovsky et al., 2007) or other bright surfaces such as desert and coastline (Remer et al., 2005). The fact that the missing AOD data is not random poses challenges for identifying the most impacted communities in health studies. Further complicating the integration of AOD and surface $PM_{2.5}$ is the choice of satellite instruments (e.g., MODIS, MISR, SeaWiFS, VIIRS, CALIOP, etc.) and their AOD retrieval algorithms (e.g., Dark Target and MAIAC products for MODIS, Deep Blue for MODIS and SeaWiFS, etc.). In addition, the relative humidity of the atmospheric column, the chemical composition, hygroscopicity and size distribution of PM in the column, and the vertical distribution of PM all affect the total uncertainty of the daily satellite-derived ground-level $PM_{2.5}$ (Ford and Heald, 2013; Jin et al., 2019a).

2.3 Data merged from ground monitors and model simulations

Numerical models of atmospheric chemistry and transport offer another powerful option for estimating near-surface $PM_{2.5}$. These models may be run at the global or regional scale, often referred to as atmospheric chemical transport models (CTMs) or photochemical grid models. These models estimate the distribution of $PM_{2.5}$ on grids whose horizontal resolution ranges from a few km (regionally) (Vaughan et al., 2004; McMillan et al., 2010) to 100's of km (globally). Examples of regional CTMs include the EPA Community Multiscale Air Quality (CMAQ; www.epa.gov/cmaq) model and the Ramboll Comprehensive Air Quality Model with Extensions (CAMx; www.camx.com). Examples of global CTMs include the GEOS-Chem model (Bey et al., 2001) and the TM5 global chemistry transport model (Huijnen et al., 2010; Van Dingenen et al., 2018). CTMs are used extensively in applications requiring predictions for policy scenarios that cannot be directly monitored due to their hypothetical nature.

Models calculate pollution concentrations over a continuous spatial domain and time period, which are free from spatiotemporal coverage limitations in monitor and satellite data. Fusing model and observational data can help to leverage the accuracy of observational data as well as the spatial and temporal coverage of models.

The EPA Fused Air Quality Surfaces Using Downscaling (FAQSD) (EPA, 2016a) is one example of the model-measurement data fusion. FAQSD constructs a surface of spatially-varying regression coefficients by comparing monitor data with modeled $PM_{2.5}$ from the CMAQ model. This surface of regression coefficients is then interpolated spatially between monitors and used to create a fused daily surface $PM_{2.5}$ exposure map (Berrocal et al., 2010a; Berrocal et al., 2012; Berrocal et al., 2010b). FAQSD has been shown to provide more accurate exposure estimates (e.g., monitors withheld from the data fusion process) than ordinary kriging of the observations alone (Berrocal et al., 2010a; Berrocal et al., 2012). In collaboration with EPA, the Centers for Disease Control and Prevention (CDC) National Environmental Public Health Tracking Network (EPHTN) has extended the methods used for FAQSD to generate continuous model-based estimates of surface $PM_{2.5}$. The EPHTN dataset (Centers for Disease Control and Prevention, 2018) is available at the census tract and county-level for the contiguous U.S. In addition to the publicly available data, numerous previous studies developed fusion algorithms that combine surface measurements and regional modeling (CMAQ) (Friberg et al., 2016; Friberg et al., 2017; Huang et al., 2018) to estimate speciated $PM_{2.5}$ concentrations at regional to national scales within the U.S.

As necessarily simplified versions of the physical atmosphere, models only represent spatial gradients on scales larger than the model grid (i.e., 12 km for the FAQSD). Areas with few or no monitoring sites are more sensitive to the model and fusion method, potentially leading to inaccuracies in the derived $PM_{2.5}$ concentrations (Berrocal et al., 2012).

2.4 Data merged from ground monitors, satellite data, and model simulations

Since there are strengths and shortcomings associated with ground monitors, satellite data, and model simulations, one method to estimate ground-level $PM_{2.5}$ is to combine all three of these sources to leverage the strengths of each one. The incorporation of model data informs the vertical distribution of aerosols in the atmosphere, and the hygroscopicity and chemical speciation of ambient PM, both key issues supporting the fusion of satellite AOD (column) with monitor data (surface). For example, high AOD may be indicative of either high levels of surface PM, or high levels of PM aloft. In this example, AOD could not distinguish between these two scenarios. The integration of model data would address this problem, with the accuracy of the surface products tied to the model simulations of aerosol vertical profiles. This approach provides a basis for estimating surface $PM_{2.5}$ from satellites, even in regions with few or no ground-based monitors (van Donkelaar et al., 2010).

Due to the incomplete spatiotemporal coverage in both monitor-based $PM_{2.5}$ and satellite AOD observations, various approaches have been developed to fill in the missing gaps. Some of them are individual methods such as kriging interpolation and land-use regression models, while other approaches are hybrid of multiple individual methods, combining model simulations and/or satellite AOD with monitor data. Two hybrid approaches are widely used – the statistical and the geoscience-based approaches. The Bayesian statistical downscaling method is a typical statistical modeling method that regresses $PM_{2.5}$-AOD relationships and downscales the coarser resolution grid-mean values to locations at higher solutions (Berrocal et al., 2012; Shaddick et al., 2018a; Shaddicket al., 2018b). The statistical modeling approach typically has lower computation cost and the ability to provide probabilistic uncertainty measures for subsequent health effect and impact studies.

The geoscience-based (also known as process-based) approach predicts $PM_{2.5}$ estimates based on monitor data, satellite AOD, as well as $PM_{2.5}$-AOD relationships from model simulations. Such approach is more computationally expensive, but usually provides higher-resolution datasets (e.g., 1 km in Dalhousie data) than the Bayesian statistical downscaling method (e.g., 12 km in EPA FAQSD). A widely used global estimate of ground-level $PM_{2.5}$ incorporating data from monitors, satellites, and an atmospheric model was developed by van Donkelaar et al. (2016). This dataset was developed by combining AOD from multiple satellite products (MISR, MODIS Dark Target, MODIS and SeaWiFS Deep Blue, and MODIS MAIAC). A GEOS-Chem simulation of atmospheric aerosols provides relationships between AOD and ground-level $PM_{2.5}$, which are further adjusted by a statistical distribution based on simulated aerosol speciation, elevation, and land-use information.

Another example of data assimilation of ground monitor and satellite data into global modeling of $PM_{2.5}$ is the Modern-Era Retrospective Analysis for Research and Applications, version 2 (MERRA-2), the latest reanalysis using the Goddard Earth Observing System, version 5 (GEOS-5) (Buchard et al., 2017). MERRA-2 data assimilate AOD from bias-corrected MODIS data, non-bias corrected MISR data and sunphotometer measurements from Aerosol Robotic Network (AERONET). In addition, the Navy Aerosol Analysis and Prediction System (NAAPS) has been used by the Naval Research Laboratory (NRL) to generate an 11-yr offline aerosol reanalysis by assimilating quality-assured and controlled MODIS and MISR AOD (Lynch et al., 2016). Other studies have developed regionally specific algorithms to calculate near-surface $PM_{2.5}$. For example, Reid et al. (2015) used machine learning to evaluate how various combinations of monitoring data, AOD, model estimates, and auxiliary datasets (land-use, traffic, and meteorology) can be used to improve the estimations of surface $PM_{2.5}$ in Northern California. Di et al. (2016) used a hybrid model based on neural network to assess $PM_{2.5}$ exposures over the U.S., and Beckerman et al. (2013) estimated the spatiotemporal variability of $PM_{2.5}$ in the U.S. using a land-use regression model.

Two sources of error exist when inferring surface mass abundance of $PM_{2.5}$ from columnar AOD: uncertainties in satellite observed AOD, and uncertainties in modeled relationships between simulated $PM_{2.5}$ and AOD. Ford and Heald (2016) estimated the contribution of the these values to uncertainties in the annual premature deaths associated with long-term $PM_{2.5}$ to be 20% for the modeled $PM_{2.5}$ - AOD relationship, and 10% for errors in the AOD retrieved from satellite instruments, based on MODIS AOD Collection 6 and 0.5°×0.667° GEOS-Chem simulations over the U.S. and China. When assimilating of AOD into model simulations, the lack of information regarding aerosol speciation and aerosol vertical distributions may lead to degraded model performance (Buchard et al., 2017). The added value of satellite data may depend on the number of existing monitors, such as the case study of Lassman et al. (2017) during the 2012 wildfire season in Washington State, which found marginal improvements by incorporating satellite data and model simulations when numerous ground monitors are present, compared with substantial improvements when fewer monitors exist.

U.S. $PM_{2.5}$ Surfaces and Health Applications

Using the methods and data discussed above, multiple research groups and agencies have developed $PM_{2.5}$ exposure estimates. A comparison among several frequently used, publicly available surface $PM_{2.5}$ datasets will be discussed, and examples will be given on how they have been used for air quality and health applications.

3.1 Major $PM_{2.5}$ exposure datasets

Table 1 shows several datasets providing spatially continuous $PM_{2.5}$ fields over the U.S. Not all of these data are directly comparable, as they may be available for different years or regions. We conduct an intercomparison of $PM_{2.5}$ among four datasets for the overlapping year of 2011: CDC WONDER (Wide-ranging Online Data for Epidemiologic Research), CDC National Environmental Public Health Tracking Network (EPHTN, also mentioned above), Dalhousie University's Atmospheric Composition Analysis group data (hereby referred to as the Dalhousie data for brevity), and the ground-based monitor data (AQS + IMPROVE). The goal of this section is to provide examples on the existing large spatial variabilities in publicly available $PM_{2.5}$ products. In fact, even though ground-based monitor data have been fused in CDC WONDER, EPHTN and Dalhousie data, there are still large differences among these datasets. We chose to intercompare their county-mean values at geocoded-address level for consistency among methods, since CDC fields were only available at the county-level.

The CDC WONDER data (Figure 1a) were developed by Al-Hamdan et al. (Al-Hamdan et al., 2014; Al-Hamdan et al., 2009) using satellite AOD from MODIS and $PM_{2.5}$ from EPA monitors, and were made available through the CDC WONDER website (http://wonder.cdc.gov/). CDC WONDER data were generated based on a regression model that derives surface $PM_{2.5}$ from satellite-based columnar AOD, and a B-spline smoothing model that generates 10-km resolution, daily, spatially continuous $PM_{2.5}$ surfaces for the contiguous U.S. by using combined AQS monitor $PM_{2.5}$ measurements and bias-corrected MODIS satellite-estimated $PM_{2.5}$ (Al-Hamdan et al., 2014; Al-Hamdan et al., 2009). This dataset provides daily $PM_{2.5}$ data at the county scale for the continental U.S in 2003–2011, easily accessible from a menu-driven online system operated by the CDC. The CDC WONDER data have been used to study associations between $PM_{2.5}$ air pollution and several adverse health effects, such as risk of sepsis hospitalization (Sarmiento et al., 2018), risk of stroke (McClure et al., 2017), incident coronary heart disease (Loop et al., 2018), cancer incidence of respiratory system (Al-Hamdan et al., 2017), cardiovascular disease mortality (Al-Hamdan et al., 2018a), and risk of autism spectrum disorder (Al-Hamdan et al., 2018b). Evaluation of the $PM_{2.5}$ estimates from CDC WONDER found a much stronger correlation with ground-based PM over the eastern and the midwestern United States than those over the western United States (Al-Hamdan et al., 2014). This same pattern is evident in comparing CDC WONDER for 2011 in Figure 1a with county-average monitoring data in Figure 1d. A potential cause for the performance limitations in CDC WONDER data is the B-spline smoothing method, which results in relatively higher predicted values particularly when ground monitors are sparse. When using a different smoothing method – the Inverse Distance Weighted (IWD) method, $PM_{2.5}$ surface estimates in California showed lower maximum values at county-level than the B-spline method (personal communication with Mohammad Al-Hamdan).

Figure 1b shows surface $PM_{2.5}$ from the CDC EPHTN, produced by the National Environmental Public Health Tracking Program in collaboration with EPA (EPHTP, also known as the Tracking Program), and based on Bayesian space-time downscaling (Berrocal et al., 2010a; Berrocal et al., 2012; Berrocal et al., 2010b). The EPHTN $PM_{2.5}$ data were previously used in epidemiology studies that track associations between $PM_{2.5}$ concentrations and a series of adverse health outcomes, including asthma-related emergency department visits, respiratory emergency department visits (Strosnider et al., 2019), exacerbation of existing asthma (Mirabelli et al., 2016), cardiovascular chronic diseases (Weber et al., 2016), chronic kidney disease and end stage renal disease (Bowe et al., 2018).

In addition, the $PM_{2.5}$ estimates from EPHTN data were incorporated in a distributed lag nonlinear model when assessing the association between extreme heat and hospitalizations (Vaidyanathan et al., 2019). Although satellite data have not been incorporated into the EPHTN data, the Tracking Program partnered with NASA and Emory University to enhance spatial coverage of $PM_{2.5}$ in the southeast U.S. (Hu et al., 2014a), and evaluated various satellite-based data products for characterizing adverse health impacts resulting from wildfire smoke $PM_{2.5}$ (Gan et al., 2017). One feature of the EPHTN data is the relatively high concentrations in the western U.S. compared with the Dalhousie and AQS+IMPROVE fields in Figure 1. This difference is likely because EPHTN data used AQS monitors but not IMPROVE monitors in the fitting. $PM_{2.5}$ concentrations in the rural areas may be overestimated when rural, low-concentration measurements from the IMPROVE network are not used, and the predictions are based on interpolation of fits from AQS monitors in urban areas.

Figure 1c shows 2011 surface $PM_{2.5}$ fields from the Dalhousie data, which are based on models, satellites, and ground monitors. The data shown in Figure 1c are from V4.NA.02, and the data products are continually updated. Van Donkelaar et al. (2010) describe the first global satellite-derived $PM_{2.5}$ dataset (V1.01), with subsequent datasets including additional satellite products (V2.01 (van Donkelaar et al., 2013)) and extending the time period of data availability (V3.01 (van Donkelaar et al., 2015)). The version shown in Figure 1c was developed for North America using AOD retrievals from multiple satellite products, combined with a GEOS-Chem simulation at 0.5°×0.67° resolution, and incorporation of local ground-based monitors through statistical fusion (V4.NA.02; (van Donkelaar et al., 2019)). This regional version builds upon updates made during development of the global product (V4.GL.02 (van Donkelaar et al., 2016)) that combine AOD from multiple satellite products based upon their relative uncertainties. The resultant 1-km $PM_{2.5}$ estimates are highly consistent (the spatial coefficient of determination (R^2) = 0.81) with global out-of-sample cross-validated $PM_{2.5}$ concentrations from ground-based monitors. A variant of these data is also available (with similar performance) for the year 2014 (Shaddick et al., 2018b) as used in the GBD (Cohen et al., 2017). These datasets are currently being updated with newer satellite products, updated models, and new monitoring networks (Snider et al., 2015). The Dalhousie V4.NA.02 data for 2011 shown in Figure 1c capture the spatial gradients of the county-level monitoring data in Figure 1d. The Dalhousie data seem to show the best agreement with the AQS+IMPROVE data in the remote areas of the western U.S. and New England, which is consistent with another comparison study (Jin et al., 2019b). This feature indicates that incorporating satellite data can be valuable for improving estimation of $PM_{2.5}$ concentrations in remote areas where monitor coverage is sparse.

For comparison, Figure 1d shows a fusion of EPA AQS $PM_{2.5}$ and IMPROVE $PM_{2.5}$ allocated to the county scale (i.e., data within the same county are averaged to a single county-mean value). The two datasets were combined to provide a more comprehensive representation of both urban and rural areas in the United States. For EPA AQS $PM_{2.5}$, only counties with $PM_{2.5}$ concentrations collected over four complete quarters in 2011 were chosen, and averaged to estimate an annual value. For IMPROVE $PM_{2.5}$, monitor locations were matched with county Federal Information Processing Standards (FIPS) code and county mean values were calculated. Then, the EPA AQS $PM_{2.5}$ and IMPROVE $PM_{2.5}$ were fused, that is, when both AQS and IMPROVE monitors occurred within a county, measurements from these two networks were averaged to derive the county mean. The agreement between the fused data fields (Figures 1a–c) with AQS-IMPROVE fused data (Figure 1d) may relate to the weight given to local data in the data fusion algorithm, and/or to the representativeness of a $PM_{2.5}$ monitor for a county average. Nevertheless, comparisons with observations can be useful for identifying differences among datasets based on quantitative evaluation metrics.

Figure 3a compares the frequency distributions of the three datasets with respect to the AQS-IMPROVE fused data. CDC WONDER consistently shows higher values than the other datasets. The Dalhousie dataset exhibits lower values of $PM_{2.5}$ overall with the widest frequency distribution (largest standard deviation in Figure 3b).

Results from our analyses of county-mean $PM_{2.5}$ estimates in 2011 are summarized in Table 2. The minimum annual county-level mass concentrations of $PM_{2.5}$ for CDC WONDER, EPHTN and Dalhousie are 7.2 $\mu g/m^3$, 4.4 $\mu g/m^3$ and 3.3 $\mu g/m^3$, respectively, with the CDC WONDER's minimum being the highest. Maximum values in each of the three datasets are similar (CDC WONDER: 14.9 $\mu g/m^3$; EPHTN: 16 $\mu g/m^3$; Dalhousie: 13.4 $\mu g/m^3$). R^2 and the normalized mean bias based on standard formula (EPA, 2018c) are calculated. Figure 2 shows the linear regression slope and intercept values. CDC WONDER exhibited the lowest R^2, 0.106, out of all the three datasets to averaged county-level AQS-IMPROVE fused data during a county-mean to county-mean comparison, and the highest normalized mean bias of 33.3%. CDC EPHTN demonstrated an R^2 of 0.649 and normalized mean bias of 12.2%. The Dalhousie dataset shows R^2 of 0.693 and normalized mean bias of 1.6% if the satellite-based data are sampled coincidentally at monitor locations from both the EPA AQS and IMPROVE networks before averaging by county and comparing, but degrades to an R^2 of 0.647 and normalized mean bias of −3.3% if county level averages are taken before comparing with the in situ monitor data, and degrades still further to an R^2 of 0.527 and normalized mean bias of −9.2% if county level averages are taken before comparing with the in situ monitor data and if the IMPROVE data are also excluded. The reduced agreement implies caution when using a limited number of primarily urban ground-based monitors to represent county averages, and motivates consideration of more spatially representative information such as from satellite and models as reviewed here. When further restricting the linear regression analyses to $PM_{2.5} < 15\ \mu g\ m^{-3}$ only, the R^2 values for CDC WONDER and Dalhousie data only increase slightly, while the R^2 value for EPHTN remains the same.

This comparison highlights the importance of methodology in estimating $PM_{2.5}$ surfaces. All three datasets used data from the EPA AQS; two used satellite AOD from the MODIS instrument; and two used advanced computer models. However, the results among these vary widely, and can be sensitive to assumptions about the spatial scale represented by individual $PM_{2.5}$ monitors. This comparison is limited to county averages of annual mean for 2011 and to only those counties with data availability over four complete quarters; so more extensive inter-comparison of $PM_{2.5}$ surfaces (including daily, grid-level and county-level comparisons for more counties and years) in future studies would provide helpful information to health and air quality organizations in selecting the appropriate data set for new applications.

3.2 $PM_{2.5}$ concentrations in global-scale estimates

The highest profile application of satellite-derived $PM_{2.5}$ fields has been the Global Burden of Diseases, Injuries, and Risk Factors Study (GBD). The GBD project continually evaluate $PM_{2.5}$ exposure using a consistent, globally applicable method representing the current state-of-the-science of data fusion of satellite, model, and monitor data.

For the 2010 GBD results reported in Lim et al. (2012), the $PM_{2.5}$ concentration estimates are described in Brauer et al. (2012) who used an average of satellite-derived $PM_{2.5}$ (van Donkelaar et al., 2010) and model (Van Dingenen et al., 2018) estimates that were recalibrated to align with in situ monitor data. For the 2013 GBD outcomes reported in Forouzanfar et al. (2015), $PM_{2.5}$ estimates from Brauer et al. (2016) were used that were based on a broader blend of satellites, a different modeling approach (van Donkelaar et al., 2015; Van Dingenen et al., 2018) and calibration against global monitoring data. More recently, the GBD 2015 results reported in Cohen et al. (2017) and Forouzanfar et al. (2016) used $PM_{2.5}$ concentrations estimated using significant methodological advances (van Donkelaar et al., 2016; Shaddick et al., 2018b). Rather than relying on a single global function to combine information from the different data sources (satellite derived product, model, and in situ monitor data), a Bayesian hierarchical model was used to combine multiple streams of information with calibration coefficients defined at the country-specific scale (where possible). This allowed the final estimate to more heavily weigh the data source that yielded the most accurate $PM_{2.5}$ estimates (as evaluated through out-of-sample cross validation) in different regions of the world.

The GBD 2016 results reported in Gakidou et al. (2017) continue to use a Bayesian hierarchical model to fuse geophysical satellite-derived $PM_{2.5}$ estimates (V4.GL.02.NoGWR (van Donkelaar et al., 2016)) with in situ $PM_{2.5}$ and PM_{10} monitor data, using predictors, modeled aerosols from the global GEOS-Chem model, a factor related to elevation and urban proximity, and random effects and correlations across these terms (Shaddick et al., 2018a). Overall, the R^2 compared to out-of-sample cross validation measurement increased from 0.64 to 0.91, and the root mean square error (RMSE) estimates reduced from 23 μg/m^3 to 12 μg/m^3, compared to GBD 2013 estimates (Shaddick et al., 2018a).

Besides differences of $PM_{2.5}$ estimates in different studies, the estimates of global exposure mortality can be affected by other factors such as causes of death being considered, regions being considered, and whether part of the $PM_{2.5}$ impact is being categorized as from indoor or outdoor $PM_{2.5}$ sources. For example, compared with the GBD studies, Burnett et al. (2018) used a different model – the Global Exposure Mortality Model (GEMM) to estimate association between outdoor $PM_{2.5}$ and non-accidental mortality, and predicted 8.9 million [95% confidence interval (CI): 7.5–10.3] deaths globally in 2015, which is 2.2 times of the prediction in the GBD (4.0 million; 95% CI: 3.3–4.8) (Forouzanfar et al., 2016).

3.3 Species and source-specific exposure estimates

Recently, an interest in identifying characteristics of $PM_{2.5}$ associated with health risks beyond total mass concentration has surged in the health and air quality fields, but progress is limited by robust evidence for the impact of $PM_{2.5}$ composition or emission sector on health outcomes (Kioumourtzoglou et al., 2015). A challenge in identifying such relationships has been the limited availability of species and source-specific exposure estimates. A review of Bates et al. (2019) summarized the recent progress for particle-bound reactive oxygen species (ROS) and oxidative potential (OP) measurements techniques. They discussed the compositional impacts on OP as well as health effects and highlighted the importance of specific emission sources including metals, organic carbon, vehicles, and biomass burning to OP. When there is a lack of measurements of OP at various times and locations, modeling approaches such as land-use regression and source impact regressions are often used (Yang et al., 2016; Bates et al., 2015; Fang et al., 2016). While models can be used to estimate species and sector-specific $PM_{2.5}$ exposures, model biases, limited resolution, and other uncertainties still limit the accuracy in model-based exposure estimates.

A number of different research groups have fused models with satellite and/or ground-based measurements, as discussed above. This same approach can be extended to the chemical speciation of aerosols available in models. For example, Ivey et al. (Ivey et al., 2017; Ivey et al., 2015) used a combination of model sensitivity analysis and receptor modeling at monitor locations to estimate source contributions to total $PM_{2.5}$ from 20 different sources, including contributions from inorganic aerosol species and metals. Zhai et al. (2016) investigated mobile source contributions to air pollution concentration fields including $PM_{2.5}$ at 250-m fine resolution using a calibrated dispersion model and ground monitor data. Their results were applied to the estimation of prenatal exposure (Pennington et al., 2017) and childhood asthma outcomes (Pennington et al., 2018) due to traffic air pollution. Lee et al. (2015) used a combination of global adjoint sensitivity modeling and satellite-derived $PM_{2.5}$ concentrations to estimate the emitted species contributing to the global total premature deaths associated with long-term exposure to $PM_{2.5}$. Rundel et al. (2015) fused monitoring data and CMAQ output and provided summaries of five major $PM_{2.5}$ species for the continental U.S., including sulfate, nitrate, total carbonaceous matter, ammonium and fine soil/crustal material. Li et al. (2017) used a combination of global modeling (GEOS-Chem) and satellite-derived $PM_{2.5}$ concentrations to estimate trends in population-weighted speciated $PM_{2.5}$ concentrations worldwide. The species considered were sulfate, nitrate, ammonium, organic aerosol, black carbon, dust, and sea-salt, and these were evaluated in comparison to speciated in situ ground monitor measurements in the U.S. The relative trends agreed to within a few percent in terms of the relative trends for most species, with the largest differences being those for natural components (sea salt and dust). Similarly, Di et al. (2016) calibrated GEOS-chem model simulations using ground monitoring data and predicted 1 km × 1 km resolution $PM_{2.5}$ speciation data on daily basis in northeastern U.S. Additionally, van Donkelaar et al. (2019) directly extend the Dalhousie University satellite-derived $PM_{2.5}$ methodology to include estimates of chemical composition. Across all species, the agreement with speciated measurements in North America had an R^2 that ranged from 0.57 to 0.96, and a slope from 0.85 to 1.05, with generally the best agreement for sulfate, ammonium and nitrate (R^2 between 0.86 – 0.96, slope between 0.99 and 1.01).

The upcoming MAIA (Multi-Angle Imager for Aerosols, preformulation ~2021) satellite-based remote sensing instrument will make radiometric and polarimetric measurements to better derive aerosol composition from space, helping to provide additional records of species and source-specific $PM_{2.5}$ to health researchers in several major urban areas worldwide (Diner et al., 2018).

Improved species and source-specific $PM_{2.5}$ surfaces will be of value for several reasons. For example, they can assist in the refinement of concentration-response relationships for epidemiological studies of the health impacts posed by particulate exposure. In addition, they can assist in identifying the $PM_{2.5}$ components or the emission sectors (e.g., transportation versus power generation) most responsible for $PM_{2.5}$'s toxicity.

3.4 Data assimilation and forecasting for episodic air pollution events

To date, most of the applications of data fusion among ground-based monitors, satellites, and/or model simulations were to support public health assessment retrospectively, since the measurements are only available for the past. To project future air quality, a conventional method is the "relative response factor" approach (EPA, 2018d), which multiplies a base year's fused concentration field by the ratio of the CMAQ model predictions between the future and base years. Such method has been applied to system development for meeting the NAAQS (Kelly et al., 2019) as well as impact analysis (EPA, 2012). However, there is clear potential to extend data fusion approaches to air quality forecasting, using satellite and ground-based data as initial conditions assimilated into the models. Health-based PM forecasts tracking smoke from wildland fires are one example of the application of data assimilation.

Wildfires are becoming increasingly important sources for $PM_{2.5}$ pollution hazards due to the large quantity of emissions (Larkin et al., 2014), the acute episodic nature of the events, the difficulties associated with controlling them, and impacts of a changing climate (Spracklen et al., 2009). In particular, for the Northwest U.S., a positive trend was found in the 98th percentiles of $PM_{2.5}$ due to the increasing total areas burned by wildfires. This is in contrast to the decreasing trend of $PM_{2.5}$ in the other areas in the contiguous U.S. (McClure and Jaffe, 2018). Several previous studies examined the adverse health effects from exposure to wildfire smoke in previous years based on observations and simulations. Rappold et al. (2017) used CMAQ model simulations with and without wildland and prescribed fires from 2008 to 2012 to quantify contribution of fire emissions to the ambient $PM_{2.5}$ levels. Their results showed that 30.5 million people in the U.S. lived in the areas where fire-emitted $PM_{2.5}$ is a large component of annual average value. Similarly, Fann et al. (2018) used CMAQ model simulations to assess the health impacts and economic value of wildland fire episodes in the U.S. from 2008–2012.

Compared with the retrospective analysis, the future-oriented forecasts for $PM_{2.5}$ emission from wildfire are even more challenging. Because of the episodic nature of wildfire emission, the forecasts would require daily or even hourly $PM_{2.5}$ estimates, rather than the annual exposure fields used in health studies like the GBD. In addition, fires typically occur in regions away from major cities where ground-based monitoring data are not always available, which imposes challenges on data assimilation.

There are multiple smoke forecasting systems in the U.S., all of which use models to provide future estimates of ground-level $PM_{2.5}$. Currently satellite data are used in these systems to inform the location, timing, and characteristics of fire. Fire detection characteristics are combined with land cover data to calculate emissions into the model, and satellite AOD is used to evaluate model performance (Schroeder et al., 2008; Larkin et al., 2009; Stein et al., 2015; Draxler and Hess, 1998; Vaughan et al., 2004; Chen et al., 2008; Herron-Thorpe et al., 2012).

Among these smoke forecasting systems, the most direct integration of satellite AOD and wildland smoke prediction is performed by the Wildland Fire Air Quality Response Program (WFAQRP), which has been developed to address smoke issues from wildfires, bringing the latest in fire emissions and smoke transport science to Incident Management Teams, health and air quality agencies, and ultimately the public. This program provides smoke forecasting expertise, deploys temporary $PM_{2.5}$ monitors to augments existing monitoring systems, and communicates information on how to protect oneself from smoke. A daily Smoke Outlook is produced, forecasting expected smoke behavior and level of impact in the region of the fire (Figure 4). These smoke outlooks are initialized with a statistical model incorporating MODIS AOD and surface $PM_{2.5}$ monitoring data to forecast the AQI for the next day (Marsha and Larkin, 2018).

Discussion and Conclusion

4.1 Remaining barriers for obtaining and applying $PM_{2.5}$ exposure for health applications

This review discusses the methods, sources, and application of spatially continuous $PM_{2.5}$ datasets derived from combinations of ground-based data, satellites, and/or atmospheric models. The data fusion products leverage the benefits of each data source, providing $PM_{2.5}$ exposure estimates over continuous spatial scales. This new resource for air quality data has already been used for health assessments, and has potential for application to research, public outreach, and environmental management. Nevertheless, several challenges remain in obtaining and applying $PM_{2.5}$ exposure for health applications. For example, missing data coverage in both ground monitors and satellite observations requires additional efforts for merging multiple data sources or interpolating data in space and time. When choosing the methods for data fusion or interpolation, users often need to weigh between the advantages and disadvantages of different methods. One may choose the efficient calculation of the Bayesian statistical downscaling method for lower spatial resolution (such as 12 km resolution in Wang et al. (2018)), while others may choose the more computational expensive methods that combine CTM, satellite and ground monitors (van Donkelaar et al., 2019), or machine learning techniques (Hu et al., 2017; Reid et al., 2015; Di et al., 2019). Methods that incorporate dispersion modeling may also be useful in some applications (Scheffe et al., 2016; Ahangar et al., 2019). Depending on the methods being used in data fusion, assimilating the ground monitor data does not guarantee similar output of surface $PM_{2.5}$, as demonstrated in our case study of four datasets in Section 3.1. Such variability among publicly available datasets calls for more intercomparison studies to contrast and explain their differences. Future intercomparison studies are recommended to isolate individual factors contributing to comparison results, including but not limited to spatiotemporal variabilities of surface $PM_{2.5}$ (e.g., seasonal variability, topography, eastern versus western U.S.), data sources being used (model, satellite and/or monitors), regression

EPA Author Manuscript

EPA Author Manuscript

of AOD – $PM_{2.5}$ relationships, representativeness of ground monitor data (e.g., weighting functions of monitors over a larger scale), spatial and temporal resolutions, etc. As end users of these $PM_{2.5}$ datasets, researchers in public health should be mindful that the agreement between fused $PM_{2.5}$ data and monitored $PM_{2.5}$ evaluated by R or R^2 are affected by multiple factors and assumptions being used in such evaluation (e.g., representativeness of monitor data, spatiotemporal interpolation, data resolutions, etc.). Varying sampling schedules for networks (i.e., higher frequency in urban areas versus lower frequency in rural areas) create another challenge when using ground monitor data as the gold standard, particularly for developing daily concentration fields. On days without rural sampling, predicted concentrations in rural areas might be overestimated because they are based on fits to predominantly urban monitoring. One way to combat this is to perform fusion on longer term monitor averages (monthly, quarterly, etc.). We recommend that researchers from both communities (i.e., data development and public health sectors) work together when applying the $PM_{2.5}$ estimates into health impacts assessments and/or air quality management actions. One example is to guide the model evaluations by the usage of $PM_{2.5}$ fields in health studies, which may be focused on a specific concentration range (e.g., lower concentrations in the rural areas versus higher concentrations in the urban areas), or a specific population. These specific targets may not be thoroughly tested by national or regional cross-validation.

4.2 Web-based Tools for $PM_{2.5}$ Exposure Analyses

Despite the benefits of these data and the rapidly advancing research in this area, there are several key steps towards wider utilization of these data. One key step is to downsize spatially continuous data based on the types of applications. Although research groups may provide global or national data, most users require a small subset of data over a particular region and time period. Online mapping tools and options that allow users to subset data prior to download can significantly reduce the data management burden on users. Another key step is to maintain and foster training tutorials and seminars on specialized mapping software. For instance, the NASA Applied Remote Sensing Training (ARSET) program has been providing in-person and online tutorials for these purposes since 2009 (NASA, 2019).

Several web-based tools are available for analyzing and predicting $PM_{2.5}$ exposure. The EPA Remote Sensing Information Gateway (RSIG), developed by U.S. EPA in collaboration with NASA, allows rapid retrieval and subsetting of satellite, model and ground-based data relevant to air quality. The RSIG website can be accessed at: https://www.epa.gov/hesc/remote-sensing-information-gateway, which provides multi-source, daily $PM_{2.5}$ data at up to 12-km horizontal resolution. Users can select only the subset of data needed for a particular application to be downloaded. RSIG can also combine multiple variables to simplify the burden of data analysis on the user. For example, if one is interested in comparing CMAQ-modeled $PM_{2.5}$ with AQS observations, the AQS observations can be subsetted and regridded to the model grid by specifying the model configuration (e.g., domain range, projection, resolution) (EPA RSIG, 2019). As of April 2018, multiple $PM_{2.5}$ datasets are available from RSIG, including the EPA AQS in-situ monitor data, standard CMAQ model simulations over the continental U.S. conducted by the U.S. EPA, the FAQSD, and the combination of ground-based monitor and model data used by the CDC EPHTN. In addition, RSIG also provides up-to-date NASA MODIS AOD, and the National

Environmental Satellite, Data and Information Service (NESDIS) Biomass Burning Emissions Data.

The University of California Berkeley's Earth Air Quality Map (http://berkeleyearth.org/air-quality-real-time-map/) provides near-real-time maps of AQI values for $PM_{2.5}$ concentrations in the U.S. and several countries and regions outside of U.S. (e.g., China, Canada, Europe, etc.) at 0.1 degree resolution. As specified on the website, preliminary data from surface station measurements are being used with automated quality control procedure, and interpolated based on Kriging method. Daily maps of $PM_{2.5}$ AQI values are available to download from June 2016 to March 2017.

When data are mapped through a web application, it can significantly reduce the burden of creating a map or plot. However, users often want the ability to create maps in a standard software platform to integrate with other aspects of their work. Currently, the netCDF is the most common format for atmospheric data, including $PM_{2.5}$ surfaces. Many programming languages, such as Python, the Interface Definition Language (IDL), MatLab, and the free National Center for Atmospheric Research (NCAR) Command Language (NCL) support netCDF data. ArcView GIS also supports netCDF, but users may have difficulty plotting large netCDF files in GIS. Because GIS platforms are so widely used among health, land planners, and policy communities, we recommend that data providers also include the standard release of GIS shapefiles as a distributed data format. Typically, shapefiles provide data in political or geographic spatial domains (e.g., U.S. counties or census tracts) rather than the grid format, which is typically used in atmospheric research.

4.3 Ongoing and future research efforts

Besides providing more guidance on the tools to potential users, improved utilization of $PM_{2.5}$ exposure datasets can be supported by increased validation. Because ground-based monitors, satellites, and models are often combined to estimated surface $PM_{2.5}$, there are few independent data sources for validation. A recent study over New York State uses independent ground-based observations from the New York City Community Air Quality Survey (NYCCAS) Program and the Saint Regis Mohawk Tribe Air Quality Program to evaluate seven $PM_{2.5}$ products (Jin et al., 2019b). Jin et al. suggest inclusion of satellite remote sensing improves the estimate of surface $PM_{2.5}$ in the remote area, but little gains over urban area. One of the networks with continuous efforts to evaluate satellite-derived $PM_{2.5}$ estimates is the publicly available Surface Particulate Matter Network SPARTAN (www.spartan-network.org) (Snider et al., 2016; Snider et al., 2015), which measures fine particle aerosol concentrations and composition continuously over multi-year periods at international sites where AOD is also measured by ground-based instruments. When validating $PM_{2.5}$ exposure data with ground-based observations, one caution is that the agreement between the fused data fields and in situ monitor data is related to the weight given to monitor data in the data fusion algorithm and the spatial and temporal scales that the in situ monitor data are assigned to represent. Certain criterion for data quality control may also cause a sampling bias.

Linking satellite observations of AOD with ground-level $PM_{2.5}$ estimates requires accurately understanding the relationship between aerosol extinction and aerosol mass abundance, which depends on multiple factors such as aerosol size distribution, hygroscopic growth (Ziemba et al., 2013; Brock et al., 2016a) and ambient relative humidity (Brock et al., 2016b). Targeted research efforts have been underway to advance understanding of these issues (Jin et al., 2019a). For example, the NASA DISCOVER-AQ aircraft campaign took place over four urban areas in the U.S. from 2011–2014, and provides extensive profiling of aerosol optical, chemical and microphysical properties at locations coincident with ground-based $PM_{2.5}$ sites. This multi-platform suite of observations is ideal for analyzing the relationship between satellite column AOD and ground-level $PM_{2.5}$ abundances (Crumeyrolle et al., 2014; Jin et al., 2019a).

While we have focused our discussion here on AOD, the most widely used metric for ambient particulates, there are other remote sensing instruments that can expand the value of satellite-based information (some of these are already in use in the data products presented here). For example, instruments aboard the Cloud-Aerosol Lidar and Infrared Pathfinder Satellite Observations (CALIPSO) provide vertical profiles of aerosol extinction with limited spatial coverage, which can be used to detect aerosols present above the surface (Ford and Heald, 2013), and to correct model biases in the vertical profiles of aerosol extinction when quality controlled retrievals are available (Geng et al., 2015; van Donkelaar et al., 2013; van Donkelaar et al., 2016; Li et al., 2015).

Ongoing research efforts have great potential to benefit spatially continuous $PM_{2.5}$ data fusion efforts. New geostationary satellites will provide improved temporal coverage, as they orbit with Earth, and can track the evolution of weather systems, wildfire smoke, urban pollution and other factors affect ground-level $PM_{2.5}$. For example, the GOES-16 satellite provides AOD at a 2-km horizontal resolution every 5 minutes over the continental U.S. and other areas in its field of view. Improvements in these data, and other upcoming satellites, hold the potential to revolutionize the role of satellite data in estimating ground-level $PM_{2.5}$. Ongoing improvement in numerical modeling of the atmosphere, supported by decreasing computational cost, will also improve these data fusion products, allowing for higher resolution model simulations. The rapid rise in low-cost PM monitors also offer opportunities for obtaining surface $PM_{2.5}$ information around the world, if low-cost monitors can be reliably calibrated.

Publicly available datasets are already supporting a wide range of air quality and health applications benefiting from spatially continuous $PM_{2.5}$ data. With the increased transparency of data products and methods, improved dissemination of data to support GIS mapping software, and plain-language communication of complex ideas have the potential to vastly expand the relevance of emerging data for health and air quality. As new users explore and evaluate these tools, their feedback to the research community can inform and improve future activities. A two-way dialogue between researchers and stakeholders, e.g., the NASA Health and Air Quality Applied Sciences Team (HAQAST, 2019) and the NASA ARSET training program (NASA, 2019), can be very helpful in defining research priorities and ensuring outcomes to serve wider needs.

Acknowledgements

The following co-authors are members of the NASA Health and Air Quality Applied Sciences Team (HAQAST): M. Diao, T. Holloway, S. O'Neill, A. Fiore (NNX16AQ20G), and D. Henze. In addition, R.V. Martin, A. van Donkelaar, X. Jin, M.Z. Al-Hamdan, A. Vaidyanathan, P. Kinney, F. Freedman, and N. Larkin are HAQAST collaborators. M. Diao, F. Freedman and M.Z. Al-Hamdan are funded by the NASA grant NNX16AQ91G. The CDC WONDER data were funded by the NASA Applied Sciences Health & Air Quality Program. The Dalhousie data are supported by the Atmospheric Composition Analysis Group at Dalhousie University in collaboration with scientists from NASA and the University of British Columbia. We appreciate technical guidance from the Wisconsin Department of Natural Resources in the interpretation and data selection for $PM_{2.5}$ in Figure 1d. The views expressed in this article are those of the authors and do not necessarily represent the views or policies of the Centers for Disease Control and Prevention, U.S. Environmental Protection Agency or other federal agencies involved in the study.

Funding

This work was supported by the National Aeronautics and Space Administration [NNX16AQ91G, NNX16AQ92G, NNX16AQ20G, NNH16AD18I, NNX16AQ26G].

About the authors

Minghui Diao is an assistant professor at San Jose State University. She received her B.S. degree from Peking University and Ph.D. degree from Princeton University. She is a member of the NASA Health and Air Quality Applied Sciences Team (HAQAST). Her current research interests include remote sensing of aerosol optical depth and PM2.5, and air quality assessment in California. For more information please see: www.cloud-research.org.

Tracey Holloway is the Gaylord Nelson Distinguished Professor at the University of Wisconsin—Madison in the Nelson Institute for Environmental Studies and the Department of Atmospheric and Oceanic Sciences. She is the Team Lead for the NASA Health and Air Quality Applied Sciences Team. For more information see hollowaygroup.org and haqast.org.

Seohyun Choi is a graduate student in Environment and Resources program at University of Wisconsin-Madison. She works with Dr. Tracey Holloway on NASA Health and Air Quality Applied Sciences Team to enhance the usage of air quality satellite data amongst public health organizations.

Susan M. O'Neill Susan O'Neill is an Air Quality Scientist with the USDA Forest Service Pacific Northwest Research Station, AirFire Team, and has a Ph.D. from the Laboratory for Atmospheric Research at Washington State University. Her research interests include fire emissions calculation and atmospheric modeling of smoke plumes from prescribed fires and wildfires.

Mohammad Al-Hamdan is a Senior Research Scientist with the Universities Space Research Association at NASA Marshall Space Flight Center in Huntsville, Alabama, USA. He received his Ph.D. and M.S. degrees in Civil and Environmental Engineering from the University of Alabama in Huntsville. His research expertise includes remote sensing and GIS applications to environmental modeling and assessment for air quality, water, urban heat island, ecological and public health applications.

EPA Author Manuscript

EPA Author Manuscript

Aaron van Donkelaar is a Research Associate in the Department of Physics and Atmospheric Science, Dalhousie University, and a Visiting Research Associate in the Department of Energy, Environmental & Chemical Engineering, Washington University in Saint Louis.

Randall V. Martin is a Professor at Washington University, Professor and Arthur B. McDonald chair of research excellence at Dalhousie University, and a research associate at the Smithsonian Astrophysical Observatory. He serves as Co-Model Scientist for the GEOS-Chem model, on multiple satellite science teams, and as the principal investigator of the Surface Particulate Matter Network (SPARTAN).

Xiaomeng Jin is a graduate student in Department of Earth and Environmental Sciences at Columbia University. She is working with Dr. Arlene Fiore working on atmospheric chemistry. Her research uses satellite observations and atmospheric chemistry models to analyze urban surface ozone and particulate matter pollution, and their sensitivities to precursor emissions.

Arlene Fiore is a professor of atmospheric chemistry in the Department of Earth and Environmental Sciences of Lamont-Doherty Earth Observatory and Columbia University and an associate faculty member of the Earth Institute. For more information please see http://blog.ldeo.columbia.edu/atmoschem/.

Daven Henze is an associate professor of mechanical engineering at the University of Colorado Boulder. He received his Ph.D. in chemical engineering from Caltech. He is a member of the NASA HAQAST team and researches the sources and fates of aerosols and trace-gases using adjoint sensitivity analysis, inverse modeling, and data assimilation.

Forrest Lacey is an Advanced Study Program postdoc fellow at the National Center for Atmospheric Research. He also worked at the University of Colorado, Boulder as a postdoc and an adjunct professor.

Patrick L. Kinney is a professor in the School of Public Health at Boston University. He received his B.S. degree in University of Colorado, Boulder, and his M.S. and ScD degrees from Harvard School of Public Health.

Frank Freedman is an adjunct faculty at San Jose State University. He received his B.S. and M.S. degrees from San Jose State University, and Ph.D. degree from Stanford University.

Narasimhan K. Larkin is a research scientist and team leader with the USDA Forest Service Pacific Northwest Research Station's AirFire Team and a member of the NASA HAQAST science team. He received his Ph.D. from the University of Washington studying climate variability. Since 2001 he has led research into wildfires, climate, and smoke, including developing emissions inventories, smoke forecasting systems, and operational decision support tools used across the United States and in other countries.

Yufei Zou is a postdoctoral research associate at Pacific Northwest National Laboratory (PNNL). Before joining PNNL, He received his Ph.D. degree in Earth and Atmospheric Sciences from Georgia Institute of Technology in 2017 and then worked at the University of

Washington in Seattle for two years. His research mainly focuses on natural hazards and extreme weather events such as large wildfires and severe air pollution associated with global climate change.

James T. Kelly is an Environmental Scientist in the Office of Air Quality Planning & Standards at the U.S. Environmental Protection Agency.

Ambarish Vaidyanathan is a health scientist with the Centers for Disease Control and Prevention. He received his Masters and Doctoral degrees in Environmental Engineering from Georgia Institute of Technology, Atlanta, GA. Dr. Vaidyanathan has broad training and work experience in epidemiology, air quality modeling, statistics, and geographic information systems. He has collaborated with NASA and NASA funded partners on remote sensing projects since 2005.

References

Ahangar FE, Freedman FR, and Venkatram A. 2019 Using Low-Cost Air Quality Sensor Networks to Improve the Spatial and Temporal Resolution of Concentration Maps. Int. J. Environ. Res. Public Health 16 (7). Multidisciplinary Digital Publishing Institute (MDPI). doi:10.3390/ijerph16071252.

Al-Hamdan AZ, Albashaireh RN, Al-Hamdan MZ, and Crosson WL. 2017 The Association of Remotely Sensed Outdoor Fine Particulate Matter with Cancer Incidence of Respiratory System in the USA. J. Environ. Sci. Heal Part A 52 (6). Taylor & Francis: 547–554. doi:10.1080/10934529.2017.1284432.

Al-Hamdan AZ, Preetha PP, Al-Hamdan MZ, Crosson WL, and Albashaireh RN. 2018a Reconnoitering the Linkage between Cardiovascular Disease Mortality and Long-Term Exposures to Outdoor Environmental Factors in the USA Using Remotely-Sensed Data. J. Environ. Sci. Heal Part A, 3 Taylor & Francis, 1–10. doi:10.1080/10934529.2018.1445083.

Al-Hamdan AZ, Preetha PP, Albashaireh RN, Al-Hamdan MZ, and Crosson WL. 2018b Investigating the Effects of Environmental Factors on Autism Spectrum Disorder in the USA Using Remotely Sensed Data. Environ. Sci. Pollut. Res 25 (8). Springer Berlin Heidelberg: 7924–7936. doi:10.1007/s11356-017-1114-8.

Al-Hamdan MZ, Crosson WL, Economou SA, Estes MG, Estes SM, Hemmings SN, Kent ST, Puckett M., Quattrochi DA, Rickman DL, Wade GM, and McClure LA 2014 Environmental public health applications using remotely sensed data. Geocarto Int 29 (1) NIH Public Access: 85–98. doi: 10.1080/10106049.2012.715209 [PubMed: 24910505]

Al-Hamdan MZ, Crosson WL, Limaye AS, Rickman DL, Quattrochi DA, Estes MG, Qualters JR, et al. 2009 Methods for Characterizing Fine Particulate Matter Using Ground Observations and Remotely Sensed Data: Potential Use for Environmental Public Health Surveillance. J. Air Waste Manage. Assoc 59 (7): 865–881. doi:10.3155/1047-3289.59.7.865.

Allen G, Sioutas C, Koutrakis P, Reiss R, Lurmann FW, and Roberts PT. 1997 Evaluation of the TEOM® Method for Measurement of Ambient Particulate Mass in Urban Areas. J. Air Waste Manag. Assoc 47 (6): 682–689. doi:10.1080/10473289.1997.10463923. [PubMed: 9180064]

Anenberg SC, Belova A, Brandt J, Fann N, Greco S, Guttikunda S, Heroux ME, et al. 2016 Survey of Ambient Air Pollution Health Risk Assessment Tools. Risk Anal. 36 (9): 1718–1736. doi:10.1111/risa.12540. [PubMed: 26742852]

Banerjee S, Carlin BP, and Gelfand AE. 2014 Hierarchical Modeling and Analysis for Spatial Data. Chapman and Hall/CRC https://www.crcpress.com/Hierarchical-Modeling-and-Analysis-for-Spatial-Data/Banerjee-Carlin-Gelfand/p/book/9781439819173.

Bates Josephine T., Weber RJ, Abrams J, Verma V, Fang T, Klein M, Strickland MJ, et al. 2015 Reactive Oxygen Species Generation Linked to Sources of Atmospheric Particulate Matter and Cardiorespiratory Effects. Environ. Sci. Technol 49 (22): 13605–13612. doi:10.1021/acs.est.5b02967. [PubMed: 26457347]

Bates Josephine Taylor, Fang T, Verma V, Zeng L, Weber RJ, Tolbert PE, Abrams J, et al. 2019 Review of Acellular Assays of Ambient Particulate Matter Oxidative Potential: Methods and Relationships with Composition, Sources, and Health Effects. Environ. Sci. Technol, 3 American Chemical Society, acs.est.8b03430. doi:10.1021/acs.est.8b03430.

Beckerman BS, Jerrett M, Serre M, Martin RV, Lee S-J, van Donkelaar A, Ross Z, Su J, and Burnett RT. 2013 A Hybrid Approach to Estimating National Scale Spatiotemporal Variability of PM $_{2.5}$ in the Contiguous United States. Environ. Sci. Technol 47 (13). American Chemical Society: 7233–7241. doi:10.1021/es400039u. [PubMed: 23701364]

Berrocal VJ, Gelfand AE, and Holland DM. 2010a A Spatio-Temporal Downscaler for Output from Numerical Models. J. Agric. Biol. Environ. Stat 15 (2): 176–197. doi:10.1007/s13253-009-0004-z. [PubMed: 21113385]

Berrocal VJ, Gelfand AE, and Holland DM. 2010b A Bivariate Space-Time Downscaler under Space and Time Misalignment. Ann. Appl. Stat 4 (4): 1942–1975. http://arxiv.org/abs/1004.1147. [PubMed: 21853015]

Berrocal VJ, Gelfand AE, and Holland DM. 2012 Space-Time Data Fusion Under Error in Computer Model Output: An Application to Modeling Air Quality. Biometrics 68 (3): 837–848. doi:10.1111/j.1541-0420.2011.01725.x. [PubMed: 22211949]

Bey I, Jacob DJ, Yantosca RM, Logan JA, Field BD, Fiore AM, Li Q, Liu HY, Mickley LJ, and Schultz MG. 2001 Global Modeling of Tropospheric Chemistry with Assimilated Meteorology: Model Description and Evaluation. J. Geophys. Res. Atmos 106 (D19). Wiley-Blackwell: 23073–23095. doi:10.1029/2001JD000807.

Bi J, Belle JH, Wang Y, Lyapustin AI, Wildani A, and Liu Y. 2019 Impacts of Snow and Cloud Covers on Satellite-Derived PM2.5 Levels. Remote Sens. Environ 221 (2). Elsevier: 665–674. doi:10.1016/J.RSE.2018.12.002. [PubMed: 31359889]

Bowe B, Xie Y, Li T, Yan Y, Xian H, and Al-Aly Z. 2018 Particulate Matter Air Pollution and the Risk of Incident CKD and Progression to ESRD. J. Am. Soc. Nephrol 29 (1). American Society of Nephrology: 218–230. doi:10.1681/ASN.2017030253. [PubMed: 28935655]

Brauer M, Amann M, Burnett RT, Cohen A, Dentener F, Ezzati M, Henderson SB, et al. 2012 Exposure Assessment for Estimation of the Global Burden of Disease Attributable to Outdoor Air Pollution. Environ. Sci. Technol 46 (2): 652–660. doi:10.1021/es2025752. [PubMed: 22148428]

Brauer M, Freedman G, Frostad J, van Donkelaar A, Martin RV, Dentener F, van Dingenen R, et al. 2016 Ambient Air Pollution Exposure Estimation for the Global Burden of Disease 2013. Environ. Sci. Technol 50 (1): 79–88. doi:10.1021/acs.est.5b03709. [PubMed: 26595236]

Brock CA, Wagner NL, Anderson BE, Attwood AR, Beyersdorf A, Campuzano-Jost P, Carlton AG, et al. 2016a Aerosol Optical Properties in the Southeastern United States in Summer - Part 1: Hygroscopic Growth. Atmos. Chem. Phys 16 (8): 4987–5007. doi:10.5194/acp-16-4987-2016.

Brock CA, Wagner NL, Anderson BE, Beyersdorf A, Campuzano-Jost P, Day DA, Diskin GS, et al. 2016b Aerosol Optical Properties in the Southeastern United States in Summer - Part 2: Sensitivity of Aerosol Optical Depth to Relative Humidity and Aerosol Parameters. Atmos. Chem. Phys 16 (8): 5009–5019. doi:10.5194/acp-16-5009-2016.

Brook RD, Rajagopalan S, Pope CA, Brook JR, Bhatnagar A, Diez-Roux AV, Holguin F, et al. 2010 Particulate Matter Air Pollution and Cardiovascular Disease: An Update to the Scientific Statement from the American Heart Association. Circulation 121 (21): 2331–2378. doi:10.1161/CIR.0b013e3181dbece1. [PubMed: 20458016]

Buchard V, Randles CA, da Silva AM, Darmenov A, Colarco PR, Govindaraju R, Ferrare R, et al. 2017 The MERRA-2 Aerosol Reanalysis, 1980 Onward. Part II: Evaluation and Case Studies. J. Clim 30 (17): 6851–6872. doi:10.1175/JCLI-D-16-0613.1.

Burnett R, Chen H, Szyszkowicz M, Fann N, Hubbell B, Pope CA, Apte JS, et al. 2018 Global Estimates of Mortality Associated with Long-Term Exposure to Outdoor Fine Particulate Matter. Proc. Natl. Acad. Sci. U. S. A 115 (38). National Academy of Sciences: 9592–9597. doi:10.1073/pnas.1803222115. [PubMed: 30181279]

Centers for Disease Control and Prevention. 2018 Home - CDC Tracking Network. https://ephtracking.cdc.gov/showHome.

EPA Author Manuscript

EPA Author Manuscript

Chen J, Vaughan J, Avise J, O'Neill S, and Lamb B. 2008 Enhancement and Evaluation of the AIRPACT Ozone and PM2.5</Inf> Forecast System for the Pacific Northwest. J. Geophys. Res. Atmos 113 (14): 1–20. doi:10.1029/2007JD009554.

Chow JC, Doraiswamy P, Watson JG, Chen L-WA, Ho SSH, and Sodeman DA. 2008 Advances in Integrated and Continuous Measurements for Particle Mass and Chemical Composition. J. Air Waste Manage. Assoc 58 (2). Taylor & Francis Group : 141–163. doi:10.3155/1047-3289.58.2.141.

Chow JC, and Watson JG. 1998 Guideline on Speciated Particulate Monitoring. https://www3.epa.gov/ttnamti1/files/ambient/pm25/spec/drispec.pdf.

Chu Y, Liu Y, Li X, Liu Z, Lu H, Lu Y, Mao Z, et al. 2016 A Review on Predicting Ground PM2.5 Concentration Using Satellite Aerosol Optical Depth. Atmosphere (Basel). 7 (10). Multidisciplinary Digital Publishing Institute: 129. doi:10.3390/atmos7100129.

Cohen AJ, Brauer M, Burnett R, Anderson HR, Frostad J, Estep K, Balakrishnan K, et al. 2017 Estimates and 25-Year Trends of the Global Burden of Disease Attributable to Ambient Air Pollution: An Analysis of Data from the Global Burden of Diseases Study 2015. Lancet 389 (10082). The Author(s). Published by Elsevier Ltd. This is an Open Access article under the CC BY 4.0 license: 1907–1918. doi:10.1016/S0140-6736(17)30505-6. [PubMed: 28408086]

Crumeyrolle S, Chen G, Ziemba L, Beyersdorf A, Thornhill L, Winstead E, Moore RH, Shook MA, Hudgins C, and Anderson BE. 2014 Factors That Influence Surface PM2.5 Values Inferred from Satellite Observations: Perspective Gained for the US Baltimore-Washington Metropolitan Area during DISCOVER-AQ. Atmos. Chem. Phys 14 (4): 2139–2153. doi:10.5194/acp-14-2139-2014.

Di Q, Amini H, Shi L, Kloog I, Silvern R, Kelly J, Sabath MB, et al. 2019 An Ensemble-Based Model of PM2.5 Concentration across the Contiguous United States with High Spatiotemporal Resolution. Environ. Int 130 (9). Pergamon: 104909. doi:10.1016/J.ENVINT.2019.104909. [PubMed: 31272018]

Di Q, Kloog I, Koutrakis P, Lyapustin A, Wang Y, and Schwartz J. 2016 Assessing PM $_{2.5}$ Exposures with High Spatiotemporal Resolution across the Continental United States. Environ. Sci. Technol 50 (9). American Chemical Society: 4712–4721. doi:10.1021/acs.est.5b06121. [PubMed: 27023334]

Di Q, Koutrakis P, and Schwartz J. 2016 A Hybrid Prediction Model for PM2.5 Mass and Components Using a Chemical Transport Model and Land Use Regression. Atmos. Environ 131 (4). Pergamon: 390–399. doi:10.1016/J.ATMOSENV.2016.02.002.

Diner DJ, Boland SW, Brauer M, Bruegge C, Burke KA, Chipman R, Di Girolamo L, et al. 2018 Advances in Multiangle Satellite Remote Sensing of Speciated Airborne Particulate Matter and Association with Adverse Health Effects: From MISR to MAIA. J. Appl. Remote Sens 12 (04). International Society for Optics and Photonics: 1. doi:10.1117/1.JRS.12.042603.

Van Dingenen R, Dentener F, Crippa M, Leitao J, Marmer E, Rao S, Solazzo E, and Valentini L. 2018 TM5-FASST: A Global Atmospheric Source-Receptor Model for Rapid Impact Analysis of Emission Changes on Air Quality and Short-Lived Climate Pollutants. Atmos. Chem. Phys 18: 16173–16211. doi:10.5194/acp-18-16173-2018.

Dominici F, Peng RD, Bell ML, Pham L, McDermott A, Zeger SL, and Samet JM. 2006 Fine Particulate Air Pollution and Hospital Admission for Cardiovascular and Respiratory Diseases. JAMA 295 (10): 1127–1134. doi:10.1001/jama.295.10.1127. [PubMed: 16522832]

van Donkelaar A, Martin RV, Brauer M, and Boys BL. 2015 Use of Satellite Observations for Long-Term Exposure Assessment of Global Concentrations of Fine Particulate Matter. Environ. Health Perspect 123 (2): 135–143. doi:10.1289/ehp.1408646. [PubMed: 25343779]

van Donkelaar A, Martin RV, Brauer M, Hsu NC, Kahn RA, Levy RC, Lyapustin A, Sayer AM, and Winker DM. 2016 Global Estimates of Fine Particulate Matter Using a Combined Geophysical-Statistical Method with Information from Satellites, Models, and Monitors. Environ. Sci. Technol 50 (7): 3762–3772. doi:10.1021/acs.est.5b05833. [PubMed: 26953851]

van Donkelaar A, Martin RV, Brauer M, Kahn R, Levy R, Verduzco C, and Villeneuve PJ. 2010 Global Estimates of Ambient Fine Particulate Matter Concentrations from Satellite-Based Aerosol Optical Depth: Development and Application. Environ. Health Perspect 118 (6): 847–855. doi:10.1289/ehp.0901623. [PubMed: 20519161] van Donkelaar A, Martin RV, Li C, and Burnett RT. 2019 Regional Estimates of Chemical Composition of Fine Particulate Matter Using a Combined Geoscience-Statistical Method with Information from Satellites, Models, and Monitors. Environ. Sci. Technol 53 (5). American Chemical Society: 2595–2611. doi:10.1021/acs.est.8b06392. [PubMed: 30698001]

van Donkelaar A, Martin RV, Spurr RJD, Drury E, Remer LA, Levy RC, and Wang J. 2013 Optimal Estimation for Global Ground-Level Fine Particulate Matter Concentrations. J. Geophys. Res. Atmos 118 (11): 5621–5636. doi:10.1002/jgrd.50479.

Draxler RR, and Hess GD. 1998 An Overview of the HYSPLIT_4 Modelling System for Trajectories, Dispersion and Deposition. Aust. Meteorol. Mag 47 (4): 295–308.

Engel-Cox JA, Holloman CH, Coutant BW, and Hoff RM. 2004 Qualitative and Quantitative Evaluation of MODIS Satellite Sensor Data for Regional and Urban Scale Air Quality. Atmos. Environ 38 (16): 2495–2509. doi:10.1016/j.atmosenv.2004.01.039.

EPA. 2012 Regulatory Impact Analysis for the Final Revisions to the National Ambient Air Quality Standards for Particulate Matter. Office of Air Quality Planning and Standards. Research Triangle Park, NC 27711 https://www3.epa.gov/ttn/ecas/regdata/RIAs/finalria.pdf.

EPA. 2016a Technical Information about Fused Air Quality Surface Using Downscaling Tool: Metadata Description. https://www.epa.gov/sites/production/files/2016-07/documents/data_fusion_meta_file_july_2016.pdf.

EPA. 2016b Air Quality Data for the CDC National Environmental Public Health Tracking Network. https://archive.epa.gov/heasd/archive-heasd/web/html/cdc.html.

EPA. 2017 Profile of Version 1 of the 2014 National Emissions Inventory. https://www.epa.gov/sites/production/files/2017-04/documents/2014neiv1_profile_final_april182017.pdf (accessed April 27, 2018).

EPA. 2018a Health and Environmental Effects of Particulate Matter (PM). https://www.epa.gov/pm-pollution/particulate-matter-pm-basics#PM (accessed April 27, 2018).

EPA. 2018b EPA AirData Air Quality Monitors. https://www.epa.gov/outdoor-air-quality-data (accessed March 10, 2019).

EPA. 2018c Air Quality Modeling Technical Support Document for the Updated 2023 Projected Ozone Design Values. https://www.epa.gov/sites/production/files/2018-06/documents/aq_modelingtsd_updated_2023_modeling_o3_dvs.pdf.

EPA. 2018d Modeling Guidance for Demonstrating Attainment of Air Quality Goals for Ozone, PM2.5, and Regional Haze. Research Triangle Park, NC https://www3.epa.gov/ttn/scram/guidance/guide/O3-PM-RH-Modeling_Guidance-2018.pdf.

EPA RSIG. 2019 https://www.epa.gov/hesc/remote-sensing-information-gateway (accessed March 10, 2019).

European Committee for Standardization (CEN). 1998 Standard EN 12341 Air quality – determination of the PM_{10} fraction of suspended particulate matter – reference method and field test procedure to demonstrate reference equivalence of measurement methods. European Standard EN 12341.

Fang T, Verma V, Bates JT, Abrams J, Klein M, Strickland MJ, Sarnat SE, et al. 2016 Oxidative Potential of Ambient Water-Soluble PM≪Sub≫2.5≪/Sub≫ in the Southeastern United States: Contrasts in Sources and Health Associations between Ascorbic Acid (AA) and Dithiothreitol (DTT) Assays. Atmos. Chem. Phys 16 (6): 3865–3879. doi:10.5194/acp-16-3865-2016.

Fann N, Alman B, Broome RA, Morgan GG, Johnston FH, Pouliot G, and Rappold AG. 2018 The Health Impacts and Economic Value of Wildland Fire Episodes in the U.S.: 2008–2012. Sci. Total Environ 610–611 (1). Elsevier: 802–809. doi:10.1016/J.SCITOTENV.2017.08.024.

Ford B, and Heald CL. 2013 Aerosol Loading in the Southeastern United States: Reconciling Surface and Satellite Observations. Atmos. Chem. Phys 13 (18): 9269–9283. doi:10.5194/acp-13-9269-2013.

Ford Bonne, and Heald CL 2016 Exploring the Uncertainty Associated with Satellite-Based Estimates of Premature Mortality Due to Exposure to Fine Particulate Matter. Atmos. Chem. Phys 16 (5): 3499–3523. doi:10.5194/acp-16-3499-2016. [PubMed: 28649266]

Forouzanfar MH, Afshin A, Alexander LT, Anderson HR, Bhutta ZA, Biryukov S, Brauer M, et al. 2016 Global, Regional, and National Comparative Risk Assessment of 79 Behavioural, Environmental and Occupational, and Metabolic Risks or Clusters of Risks, 1990–2015: A Systematic Analysis for the Global Burden of Disease Study 2015. Lancet 388 (10053): 1659–1724. doi:10.1016/S0140-6736(16)31679-8. [PubMed: 27733284]

Forouzanfar MH, Alexander L, Anderson HR, Bachman VF, Biryukov S, Brauer M, Burnett R, et al. 2015 Global, Regional, and National Comparative Risk Assessment of 79 Behavioural, Environmental and Occupational, and Metabolic Risks or Clusters of Risks in 188 Countries, 1990–2013: A Systematic Analysis for the Global Burden of Disease Study 2013. Lancet 386 (10010). Elsevier: 2287–2323. doi:10.1016/S0140-6736(15)00128-2. [PubMed: 26364544]

Friberg MD, Kahn RA, Holmes HA, Chang HH, Sarnat SE, Tolbert PE, Russell AG, and Mulholland JA. 2017 Daily Ambient Air Pollution Metrics for Five Cities: Evaluation of Data-Fusion-Based Estimates and Uncertainties. Atmos. Environ 158 (2). Elsevier Ltd: 36–50. doi:10.1016/j.atmosenv.2017.03.022.

Friberg MD, Zhai X, Holmes HA, Chang HH, Strickland MJ, Sarnat SE, Tolbert PE, Russell AG, and Mulholland JA. 2016 Method for Fusing Observational Data and Chemical Transport Model Simulations To Estimate Spatiotemporally Resolved Ambient Air Pollution. Environ. Sci. Technol 50 (7). American Chemical Society: 3695–3705. doi:10.1021/acs.est.5b05134. [PubMed: 26923334]

Gakidou E, Afshin A, Abajobir AA, Abate KH, Abbafati C, Abbas KM, Abd-Allah F, et al. 2017 Global, Regional, and National Comparative Risk Assessment of 84 Behavioural, Environmental and Occupational, and Metabolic Risks or Clusters of Risks, 1990–2016: A Systematic Analysis for the Global Burden of Disease Study 2016. Lancet (London, England) 390 (10100). Elsevier: 1345–1422. doi:10.1016/S0140-6736(17)32366-8.

Gan RW, Ford B, Lassman W, Pfister G, Vaidyanathan A, Fischer E, Volckens J, Pierce JR, and Magzamen S. 2017 Comparison of Wildfire Smoke Estimation Methods and Associations with Cardiopulmonary-Related Hospital Admissions. GeoHealth 1 (3): 122–136. doi:10.1002/2017GH000073. [PubMed: 28868515]

Geng G, Zhang Q, Martin RV, van Donkelaar A, Huo H, Che H, Lin J, and He K. 2015 Estimating Long-Term PM2.5 Concentrations in China Using Satellite-Based Aerosol Optical Depth and a Chemical Transport Model. Remote Sens. Environ 166 Elsevier Inc: 262–270. doi:10.1016/j.rse.2015.05.016.

Gupta P, and Christopher SA. 2009 Particulate Matter Air Quality Assessment Using Integrated Surface, Satellite, and Meteorological Products: 2. A Neural Network Approach. J. Geophys. Res. Atmos 114 (20): 1–14. doi:10.1029/2008JD011497.

Gupta P, Christopher SA, Wang J, Gehrig R, Lee Y, and Kumar N. 2006 Satellite Remote Sensing of Particulate Matter and Air Quality Assessment over Global Cities. Atmos. Environ 40 (30): 5880–5892. doi:10.1016/j.atmosenv.2006.03.016.

Haikerwal A, Akram M, Del Monaco A, Smith K, Sim MR, Meyer M, Tonkin AM, Abramson MJ, and Dennekamp M. 2015 Impact of Fine Particulate Matter (PM2.5) Exposure during Wildfires on Cardiovascular Health Outcomes. J. Am. Heart Assoc 4 (7): 1–10. doi:10.1161/JAHA.114.001653.

HAQAST N. 2019 NASA HEALTH AND AIR QUALITY APPLIED SCIENCES TEAM. https://haqast.org/ (accessed March 10, 2019).

Henderson SB, and Johnston FH. 2012 Measures of Forest Fire Smoke Exposure and Their Associations with Respiratory Health Outcomes. Curr. Opin. Allergy Clin. Immunol 12 (3): 221–227. doi:10.1097/ACI.0b013e328353351f. [PubMed: 22475995]

Hering S, and Cass G. 1999 The Magnitude of Bias in the Measurement of PM2.5 Arising from Volatilization of Particulate Nitrate from Teflon Filters. J. Air Waste Manag. Assoc 49 (6): 725–733. doi:10.1080/10473289.1999.10463843. [PubMed: 26355375]

Herron-Thorpe FL, Mount GH, Emmons LK, Lamb BK, Chung SH, and Vaughan JK. 2012 Regional Air-Quality Forecasting for the Pacific Northwest Using MOPITT/TERRA Assimilated Carbon Monoxide MOZART-4 Forecasts as a near Real-Time Boundary Condition. Atmos. Chem. Phys 12 (12): 5603–5615. doi:10.5194/acp-12-5603-2012.

Hoek G, Krishnan RM, Beelen R, Peters A, Ostro B, Brunekreef B, and Kaufman JD. 2013 Long-Term Air Pollution Exposure and Cardio- Respiratory Mortality: A Review. Environ. Heal 12 (1): 43. doi:10.1186/1476-069X-12-43.

EPA Author Manuscript

EPA Author Manuscript

Hoff RM, and Christopher SA. 2009 Remote Sensing of Particulate Pollution from Space: Have We Reached the Promised Land? J. Air Waste Manage. Assoc 59 (6). Taylor & Francis Group : 645–675. doi:10.3155/1047-3289.59.6.645.

Holland DM, Cox WM, Scheffe R, Cimorelli AJ, Nychka D, and Hopke PK. 2003 Spatial Prediction of Air Quality Data. Environ. Manag, 31–35. https://cfpub.epa.gov/si/si_public_record_report.cfm?dirEntryId=66294&Lab=NERL.

Hu X, Belle JH, Meng X, Wildani A, Waller LA, Strickland MJ, and Liu Y. 2017 Estimating PM $_{2.5}$ Concentrations in the Conterminous United States Using the Random Forest Approach. Environ. Sci. Technol 51 (12). American Chemical Society: 6936–6944. doi:10.1021/acs.est.7b01210. [PubMed: 28534414]

Hu X, Waller LA, Lyapustin A, Wang Y, Al-Hamdan MZ, Crosson WL, Estes MG, et al. 2014a Estimating Ground-Level PM2.5 Concentrations in the Southeastern United States Using MAIAC AOD Retrievals and a Two-Stage Model. Remote Sens. Environ 140 (2014). Elsevier Inc.: 220–232. doi:10.1016/j.rse.2013.08.032.

Hu X, Waller LA, Lyapustin A, Wang Y, and Liu Y. 2014b 10-Year Spatial and Temporal Trends of PM≪Sub≫2.5≪/Sub≫ Concentrations in the Southeastern US Estimated Using High-Resolution Satellite Data. Atmos. Chem. Phys 14 (12): 6301–6314. doi:10.5194/acp-14-6301-2014. [PubMed: 28966656]

Huang R, Zhai X, Ivey CE, Friberg MD, Hu X, Liu Y, Di Q, Schwartz J, Mulholland JA, and Russell AG. 2018 Air Pollutant Exposure Field Modeling Using Air Quality Model-Data Fusion Methods and Comparison with Satellite AOD-Derived Fields: Application over North Carolina, USA. Air Qual. Atmos. Heal 11 (1): 11–22. doi:10.1007/s11869-017-0511-y.

Huijnen V, Williams J, van Weele M, van Noije T, Krol M, Dentener F, Segers A, et al. 2010 The Global Chemistry Transport Model TM5: Description and Evaluation of the Tropospheric Chemistry Version 3.0. Geosci. Model Dev 3 (2): 445–473. doi:10.5194/gmd-3-445-2010.

Ivey CE, Holmes HA, Hu YT, Mulholland JA, and Russell AG. 2015 Development of PM2.5 Source Impact Spatial Fields Using a Hybrid Source Apportionment Air Quality Model. Geosci. Model Dev 8 (7): 2153–2165. doi:10.5194/gmd-8-2153-2015.

Ivey C, Holmes H, Shi G, Balachandran S, Hu Y, and Russell AG. 2017 Development of PM $_{2.5}$ Source Profiles Using a Hybrid Chemical Transport-Receptor Modeling Approach. Environ. Sci. Technol 51 (23). American Chemical Society: 13788–13796. doi:10.1021/acs.est.7b03781. [PubMed: 29110467]

Jin X, Fiore AM, Curci G, Lyapustin A, Civerolo K, Ku M, van Donkelaar A, and Martin RV. 2019a Assessing Uncertainties of a Geophysical Approach to Estimate Surface Fine Particulate Matter Distributions from Satellite-Observed Aerosol Optical Depth. Atmos. Chem. Phys 19 (1): 295–313. doi:10.5194/acp-19-295-2019.

Jin X, Fiore AM, Civerolo K, Bi J, Liu Y, Van Donkelaar A, Martin R, et al. 2019b Comparison of Multiple $PM_{2.5}$ Exposure Products for Estimating Health Benefits of Emission Controls over New York State, USA. Environ. Res. Lett, 6 IOP Publishing. doi:10.1088/1748-9326/ab2dcb.

Keller JP, and Peng RD. 2019 Error in Estimating Area-level Air Pollution Exposures for Epidemiology Environmetrics, 5 John Wiley & Sons, Ltd, e2573. doi:10.1002/env.2573.

Kelly JT, Jang CJ, Timin B, Gantt B, Reff A, Zhu Y, Long S, and Hanna A. 2019 A System for Developing and Projecting PM2.5 Spatial Fields to Correspond to Just Meeting National Ambient Air Quality Standards Atmos. Environ X 2 (4). Elsevier: 100019. doi:10.1016/J.AEAOA.2019.100019.

Kim YH, Warren SH, Krantz QT, King C, Jaskot R, Preston WT, George BJ, et al. 2018 Mutagenicity and Lung Toxicity of Smoldering vs. Flaming Emissions from Various Biomass Fuels: Implications for Health Effects from Wildland Fires. Environ. Health Perspect 126 (01): 017011. doi:10.1289/EHP2200. [PubMed: 29373863]

Kioumourtzoglou M-A, Austin E, Koutrakis P, Dominici F, Schwartz J, and Zanobetti A. 2015 PM2.5 and Survival among Older Adults: Effect Modification by Particulate Composition. HHS Public Access 26 (3): 321–327. doi:10.1097/EDE.0000000000000269.

Klimont Z, Kupiainen K, Heyes C, Purohit P, Cofala J, Rafaj P, Borken-Kleefeld J, and Schöpp W. 2017 Supplement of Global Anthropogenic Emissions of Particulate Matter Including Black Carbon. Atmos. Chem. Phys 17 (14): 8681–8723. doi:10.5194/acp-17-8681-2017.

Kloog I, Chudnovsky AA, Just AC, Nordio F, Koutrakis P, Coull BA, Lyapustin A, Wang Y, and Schwartz J. 2014 A New Hybrid Spatio-Temporal Model for Estimating Daily Multi-Year PM2.5 Concentrations across Northeastern USA Using High Resolution Aerosol Optical Depth Data. Atmos. Environ 95: 581–590. doi:10.1016/j.atmosenv.2014.07.014.

Koelemeijer RBA, Homan CD, and Matthijsen J. 2006 Comparison of Spatial and Temporal Variations of Aerosol Optical Thickness and Particulate Matter over Europe. Atmos. Environ 40 (27): 5304–5315. doi:10.1016/j.atmosenv.2006.04.044.

Kokhanovsky AA, Breon F-M, Cacciari A, Carboni E, Diner D, Di Nicolantonio W, Grainger RG, et al. 2007 Aerosol Remote Sensing over Land: A Comparison of Satellite Retrievals Using Different Algorithms and Instruments. Atmos. Res 85 (3–4). Elsevier: 372–394. doi:10.1016/J.ATMOSRES.2007.02.008.

Krewski D, Jerrett M, Burnett RT, Ma R, Hughes E, Shi Y, Turner MC, et al. 2009 Extended Follow-up and Spatial Analysis of the American Cancer Society Study Linking Particulate Air Pollution and Mortality. Res. Rep. Health. Eff. Inst, no. 140 (5): 5–114; discussion 115–36 http://www.ncbi.nlm.nih.gov/pubmed/19627030.

Laden F, Neas LM, Dockery DW, and Schwartz J. 2000 Association of Fine Particulate Matter from Different Sources with Daily Mortality in Six U.S. Cities. Environ. Health Perspect 108 (10). National Institute of Environmental Health Science: 941–7. doi:10.1289/ehp.00108941. [PubMed: 11049813]

Larkin NK, O'Neill SM, Solomon R, Raffuse S, Strand T, Sullivan DC, Krull C, Rorig M, Peterson J, and Ferguson SA. 2009 The BlueSky Smoke Modeling Framework. Int. J. Wildl. Fire 18 (8): 906–920. doi:10.1071/WF07086.

Larkin NK, Raffuse SM, and Strand TM. 2014 Wildland Fire Emissions, Carbon, and Climate: U.S. Emissions Inventories. For. Ecol. Manage 317 Elsevier B.V: 61–69. doi:10.1016/j.foreco.2013.09.012.

Lassman W, Ford B, Gan RW, Pfister G, Magzamen S, Fischer EV, and Pierce JR. 2017 Spatial and Temporal Estimates of Population Exposure to Wildfire Smoke during the Washington State 2012 Wildfire Season Using Blended Model, Satellite, and in Situ Data. GeoHealth 1 (3). Wiley-Blackwell: 106–121. doi:10.1002/2017GH000049. [PubMed: 32158985]

Lee CJ, Martin RV, Henze DK, Brauer M, Cohen A, and van Donkelaar A. 2015 Response of Global Particulate-Matter-Related Mortality to Changes in Local Precursor Emissions. Environ. Sci. Technol 49 (7): 4335–4344. doi:10.1021/acs.est.5b00873. [PubMed: 25730303]

Lee M, Kloog I, Chudnovsky A, Lyapustin A, Wang Y, Melly S, Coull B, Koutrakis P, and Schwartz J. 2016 Spatiotemporal Prediction of Fine Particulate Matter Using High-Resolution Satellite Images in the Southeastern US 2003–2011. J. Expo. Sci. Environ. Epidemiol 26 (4). NIH Public Access: 377–84. doi:10.1038/JES.2015.41. [PubMed: 26082149]

Lennartson EM, Wang J, Gu J, Castro Garcia L, Ge C, Gao M, Choi M, et al. 2018 Diurnal Variation of Aerosol Optical Depth and PM≪Sub≫2.5≪/Sub≫ in South Korea: A Synthesis from AERONET, Satellite (GOCI), KORUS-AQ Observation, and the WRF-Chem Model. Atmos. Chem. Phys 18 (20): 15125–15144. doi:10.5194/acp-18-15125-2018.

Li C, Martin RV, Boys BL, van Donkelaar A, and Ruzzante S. 2016 Evaluation and Application of Multi-Decadal Visibility Data for Trend Analysis of Atmospheric Haze. Atmos. Chem. Phys 16 (4): 2435–2457. doi:10.5194/acp-16-2435-2016.

Li C, Martin RV, van Donkelaar A, Boys BL, Hammer MS, Xu JW, Marais EA, et al. 2017 Trends in Chemical Composition of Global and Regional Population-Weighted Fine Particulate Matter Estimated for 25 Years. Environ. Sci. Technol 51 (19): 11185–11195. doi:10.1021/acs.est.7b02530. [PubMed: 28891283]

Li J, Carlson BE, and Lacis AA. 2015 How Well Do Satellite AOD Observations Represent the Spatial and Temporal Variability of PM2.5 Concentration for the United States? Atmos. Environ 102 (2). Pergamon: 260–273. doi:10.1016/J.ATMOSENV.2014.12.010.

Lim SS, Vos T, Flaxman AD, Danaei G, Shibuya K, Adair-Rohani H, AlMazroa MA, et al. 2012 A Comparative Risk Assessment of Burden of Disease and Injury Attributable to 67 Risk Factors and Risk Factor Clusters in 21 Regions, 1990–2010: A Systematic Analysis for the Global Burden of Disease Study 2010. Lancet 380 (9859): 2224–2260. doi:10.1016/S0140-6736(12)61766-8. [PubMed: 23245609]

Lin H, Guo Y, Di Q, Zheng Y, Kowal P, Xiao J, Liu T, et al. 2017 Ambient PM 2.5 and Stroke. Stroke 48 (5): 1191–1197. doi:10.1161/STROKEAHA.116.015739. [PubMed: 28386038]

Liu JC, Pereira G, Uhl SA, Bravo MA, and Bell ML. 2015 A Systematic Review of the Physical Health Impacts from Non-Occupational Exposure to Wildfire Smoke. Environ. Res 136 (1): 120–132. doi:10.1016/j.envres.2014.10.015. [PubMed: 25460628]

Liu Y, Franklin M, Kahn R, and Koutrakis P. 2007 Using Aerosol Optical Thickness to Predict Ground-Level PM2.5 Concentrations in the St. Louis Area: A Comparison between MISR and MODIS. Remote Sens. Environ 107 (1–2): 33–44. doi:10.1016/j.rse.2006.05.022.

Liu Y, Paciorek CJ, and Koutrakis P. 2009 Estimating Regional Spatial and Temporal Variability of PM(2.5) Concentrations Using Satellite Data, Meteorology, and Land Use Information. Environ. Health Perspect 117 (6). National Institute of Environmental Health Science: 886–92. doi:10.1289/ehp.0800123. [PubMed: 19590678]

Liu Y, Sarnat JA, Kilaru V, Jacob DJ, and Koutrakis P. 2005 Estimating Ground-Level PM $_{2.5}$ in the Eastern United States Using Satellite Remote Sensing. Environ. Sci. Technol 39 (9): 3269–3278. doi:10.1021/es049352m. [PubMed: 15926578]

Loop MS, McClure LA, Levitan EB, Al-Hamdan MZ, Crosson WL, and Safford MM. 2018 Fine Particulate Matter and Incident Coronary Heart Disease in the REGARDS Cohort. Am. Heart J 197 (3). Mosby: 94–102. doi:10.1016/J.AHJ.2017.11.007. [PubMed: 29447790]

Lynch P, Reid JS, Westphal DL, Zhang J, Hogan TF, Hyer EJ, Curtis CA, et al. 2016 An 11-Year Global Gridded Aerosol Optical Thickness Reanalysis (v1.0) for Atmospheric and Climate Sciences. Geosci. Model Dev 9 (4): 1489–1522. doi:10.5194/gmd-9-1489-2016.

Ma Z, Hu X, Huang L, Bi J, and Liu Y. 2014 Estimating Ground-Level PM2.5 in China Using Satellite Remote Sensing. Environ. Sci. Technol 48 (13): 7436–7444. doi:10.1021/es5009399. [PubMed: 24901806]

Malley CS, Kuylenstierna JCI, Vallack HW, Henze DK, Blencowe H, and Ashmore MR. 2017 Preterm Birth Associated with Maternal Fine Particulate Matter Exposure: A Global, Regional and National Assessment. Environ. Int 101 (4): 173–182. doi:10.1016/j.envint.2017.01.023. [PubMed: 28196630]

Malm WC, Sisler JF, Huffman D, Eldred RA, and Cahill TA. 1994 Spatial and Seasonal Trends in Particle Concentration and Optical Extinction in the United States. J. Geophys. Res 99 (D1). Wiley-Blackwell: 1347. doi:10.1029/93JD02916.

Marsha A, and Larkin NK. 2018 A Statistical Model for Predicting PM2.5 for the Western United States. To Be Submitt. to J. Air Waste Manag. Assoc

McClure CD, and Jaffe DA. 2018 US Particulate Matter Air Quality Improves except in Wildfire-Prone Areas. Proc. Natl. Acad. Sci. U. S. A 115 (31). National Academy of Sciences: 7901–7906. doi:10.1073/pnas.1804353115. [PubMed: 30012611]

McClure LA, Loop MS, Crosson W, Kleindorfer D, Kissela B, and Al-Hamdan M. 2017 Fine Particulate Matter (PM 2.5) and the Risk of Stroke in the REGARDS Cohort. J. Stroke Cerebrovasc. Dis 26 (8): 1739–1744. doi:10.1016/j.jstrokecerebrovasdis.2017.03.041. [PubMed: 28456465]

McMillan NJ, Holland DM, Morara M, and Feng J. 2010 Combining Numerical Model Output and Particulate Data Using Bayesian Space-Time Modeling. Environmetrics 21 (2). Wiley-Blackwell: 48–65. doi:10.1002/env.984.

Menut L, Bessagnet B, Colette A, and Khvorostiyanov D. 2013 On the Impact of the Vertical Resolution on Chemistry-Transport Modelling. Atmos. Environ 67 (3). Pergamon: 370–384. doi:10.1016/J.ATMOSENV.2012.11.026.

Mirabelli MC, Vaidyanathan A, Flanders WD, Qin X, and Garbe P. 2016 Outdoor PM $_{2.5}$, Ambient Air Temperature, and Asthma Symptoms in the Past 14 Days among Adults with Active Asthma. Environ. Health Perspect 124 (12): 1882–1890. doi:10.1289/EHP92. [PubMed: 27385358]

Munoz-Alpizar R, Pavlovic R, Moran M, Chen J, Gravel S, Henderson S, Ménard S, et al. 2017 Multi-Year (2013–2016) PM2.5 Wildfire Pollution Exposure over North America as Determined from Operational Air Quality Forecasts. Atmosphere (Basel). 8 (12). Multidisciplinary Digital Publishing Institute: 179. doi:10.3390/atmos8090179.

NASA. 2019 Applied Remote Sensing Training (ARSET). https://arset.gsfc.nasa.gov/ (accessed March 7, 2019).

Ni L, Chuang C-C, and Zuo L. 2015 Fine Particulate Matter in Acute Exacerbation of COPD. Front. Physiol 6 (10): 294. doi:10.3389/fphys.2015.00294. [PubMed: 26557095]

Noble CA, Vanderpool RW, Peters TM, Frank FM, Gemmill DB, and Wiener RW. 2010 Federal Reference and Equivalent Methods for Measuring Fine Particulate Matter. Aerosol Sci. Technol 34 (5): 457–464. doi:10.1080/02786820121582.

Ouyang W, Guo B, Cai G, Li Q, Han S, Liu B, and Liu X. 2015 The Washing Effect of Precipitation on Particulate Matter and the Pollution Dynamics of Rainwater in Downtown Beijing. Sci. Total Environ 505 (2): 306–314. doi:10.1016/j.scitotenv.2014.09.062. [PubMed: 25461032]

Paciorek CJ, Liu Y, Moreno-Macias H, and Kondragunta S. 2008 Spatiotemporal Associations between GOES Aerosol Optical Depth Retrievals and Ground-Level PM2.5. Environ. Sci. Technol 42 (15): 5800–6. [PubMed: 18754512]

Paulu C, and Smith AE. 2008 Tracking Associations Between Ambient Ozone and Asthma-Related Emergency Department Visits Using Case-Crossover Analysis. J. Public Heal. Manag. Pract 14 (6): 581–591. doi:10.1097/01.PHH.0000338371.53242.0e.

Pennington AF, Strickland MJ, Klein M, Zhai X, Bates JT, Drews-Botsch C, Hansen C, Russell AG, Tolbert PE, and Darrow LA. 2018 Exposure to Mobile Source Air Pollution in Early-Life and Childhood Asthma Incidence. Epidemiology 29 (1): 22–30. doi:10.1097/EDE.0000000000000754. [PubMed: 28926373]

Pennington AF, Strickland MJ, Klein M, Zhai X, Russell AG, Hansen C, and Darrow LA. 2017 Measurement Error in Mobile Source Air Pollution Exposure Estimates Due to Residential Mobility during Pregnancy. J. Expo. Sci. Environ. Epidemiol 27 (5): 513–520. doi:10.1038/jes.2016.66. [PubMed: 27966666]

Peters A, Dockery DW, Muller JE, and Mittleman MA. 2001 Increase Particulate Air Pollution and the Triggering of Myocardial Infarction. Circulation 103 (23): 2810–2815. doi:10.1161/01.cir.99.21.2737. [PubMed: 11401937]

Pope CA, and Dockery DW. 2006 Health Effects of Fine Particulate Air Pollution: Lines That Connect. J. Air Waste Manage. Assoc 56 (6). Taylor & Francis Group : 709–742. doi:10.1080/10473289.2006.10464485.

Pope CA III, Burnett RT, Thun MJ, Calle EE, Krewski D, Ito K, and Thurston GD 2002 Lung Cancer, Cardiopulmonary Mortality, and Long-Term Exposure to Fine Particulate Air Pollution. JAMA 287 (9). American Medical Association: 1132. doi:10.1001/jama.287.9.1132. [PubMed: 11879110]

Rappold AG, Reyes J, Pouliot G, Cascio WE, and Diaz-Sanchez D. 2017 Community Vulnerability to Health Impacts of Wildland Fire Smoke Exposure. Environ. Sci. Technol 51 (12). American Chemical Society: 6674–6682. doi:10.1021/acs.est.6b06200. [PubMed: 28493694]

Rappold AG, Stone SL, Cascio WE, Neas LM, Kilaru VJ, Carraway MS, Szykman JJ, et al. 2011 Peat Bog Wildfire Smoke Exposure in Rural North Carolina Is Associated with Cardiopulmonary Emergency Department Visits Assessed through Syndromic Surveillance. Enviromental Heal. Perpectives 119 (10): 1415–1420. doi:10.1289/ehp.1003206.

Reid CE, Brauer M, Johnston FH, Jerrett M, Balmes JR, and Elliott CT. 2016 Critical Review of Health Impacts of Wildfire Smoke Exposure. Environ. Health Perspect 124 (9): 1334–43. doi:10.1289/ehp.1409277. [PubMed: 27082891]

Reid CE, Jerrett M, Petersen ML, Pfister GG, Morefield PE, Tager IB, Raffuse SM, and Balmes JR. 2015 Spatiotemporal Prediction of Fine Particulate Matter during the 2008 Northern California Wildfires Using Machine Learning. Environ. Sci. Technol 49 (6): 3887–3896. doi:10.1021/es505846r. [PubMed: 25648639]

Remer LA, Kaufman YJ, Tanré D, Mattoo S, Chu DA, Martins JV, Li R-R, et al. 2005 The MODIS Aerosol Algorithm, Products, and Validation. J. Atmos. Sci 62 (4): 947–973. doi:10.1175/JAS3385.1.

Rundel CW, Schliep EM, Gelfand AE, and Holland DM. 2015 A Data Fusion Approach for Spatial Analysis of Speciated PM $_{2.5}$ across Time. Environmetrics 26 (8). John Wiley & Sons, Ltd: 515–525. doi:10.1002/env.2369.

Sarmiento EJ, Moore JX, McClure LA, Griffin R, Al-Hamdan MZ, and Wang HE. 2018 Fine Particulate Matter Pollution and Risk of Community-Acquired Sepsis. Int. J. Environ. Res. Public Health 15 (4). Multidisciplinary Digital Publishing Institute (MDPI). doi:10.3390/ijerph15040818.

Scheffe RD, Strum M, Phillips SB, Thurman J, Eyth A, Fudge S, Morris M, Palma T, and Cook R. 2016 Hybrid Modeling Approach to Estimate Exposures of Hazardous Air Pollutants (HAPs) for the National Air Toxics Assessment (NATA). Environ. Sci. Technol 50 (22): 12356–12364. doi:10.1021/acs.est.6b04752. [PubMed: 27779870]

Schroeder W, Ruminski M, Csiszar I, Giglio L, Prins E, Schmidt C, and Morisette J. 2008 Validation Analyses of an Operational Fire Monitoring Product: The Hazard Mapping System. Int. J. Remote Sens 29 (20). Taylor & Francis : 6059–6066. doi:10.1080/01431160802235845.

Shaddick G, Thomas ML, Amini H, Broday D, Cohen A, Frostad J, Green A, et al. 2018a Data Integration for the Assessment of Population Exposure to Ambient Air Pollution for Global Burden of Disease Assessment. Environ. Sci. Technol 52 (16). American Chemical Society: 9069–9078. doi:10.1021/acs.est.8b02864. [PubMed: 29957991]

Shaddick G, Thomas ML, Green A, Brauer M, van Donkelaar A, Burnett R, Chang HH, et al. 2018b Data Integration Model for Air Quality: A Hierarchical Approach to the Global Estimation of Exposures to Ambient Air Pollution. J. R. Stat. Soc. Ser. C Appl. Stat 67 (1): 231–253. doi:10.1111/rssc.12227.

Snider G, Weagle CL, Martin RV, van Donkelaar A, Conrad K, Cunningham D, Gordon C, et al. 2015 SPARTAN: A Global Network to Evaluate and Enhance Satellite-Based Estimates of Ground-Level Particulate Matter for Global Health Applications. Atmos. Meas. Tech 8 (1): 505–521. doi:10.5194/amt-8-505-2015.

Snider Graydon, Weagle CL, Murdymootoo KK, Ring A, Ritchie Y, Stone E, Walsh A, et al. 2016 Variation in Global Chemical Composition of PM2.5: Emerging Results from SPARTAN. Atmos. Chem. Phys 16 (15): 9629–9653. doi:10.5194/acp-16-9629-2016.

Solomon PA, Crumpler D, Flanagan JB, Jayanty RKM, Rickman EE, and McDade CE. 2014 U.S. National PM 2.5 Chemical Speciation Monitoring Networks—CSN and IMPROVE: Description of Networks. J. Air Waste Manage. Assoc 64 (12). Taylor & Francis: 1410–1438. doi:10.1080/10962247.2014.956904.

Spracklen DV, Mickley LJ, Logan JA, Hudman RC, Yevich R, Flannigan MD, and Westerling AL. 2009 Impacts of Climate Change from 2000 to 2050 on Wildfire Activity and Carbonaceous Aerosol Concentrations in the Western United States. J. Geophys. Res 114 (D20). Wiley-Blackwell: D20301. doi:10.1029/2008JD010966.

State of Global Air 2018 Special Report. 2018 Boston, Mass https://www.stateofglobalair.org/sites/default/files/soga-2018-report.pdf.

Stefanidou M, Athanaselis S, and Spiliopoulou C. 2008 Health Impacts of Fire Smoke Inhalation. Inhal. Toxicol 20 (8): 761–766. doi:10.1080/08958370801975311. [PubMed: 18569098]

Stein AF, Draxler RR, Rolph GD, Stunder BJB, Cohen MD, and Ngan F. 2015 Noaa's Hysplit Atmospheric Transport and Dispersion Modeling System. Bull. Am. Meteorol. Soc 96 (12): 2059–2077. doi:10.1175/BAMS-D-14-00110.1.

Strosnider HM, Chang HH, Darrow LA, Liu Y, Vaidyanathan A, and Strickland MJ. 2018 Age-Specific Associations of Ozone and PM $_{2.5}$ with Respiratory Emergency Department Visits in the US. Am. J. Respir. Crit. Care Med, 10, rccm.201806–1147OC. doi:10.1164/rccm.201806-1147OC.

Talbot TO, Haley VB, Dimmick WF, Paulu C, Talbott EO, and Rager J. 2009 Developing Consistent Data and Methods to Measure the Public Health Impacts of Ambient Air Quality for Environmental Public Health Tracking: Progress to Date and Future Directions. Air Qual. Atmos. Health 2 (4). Springer: 199–206. doi:10.1007/s11869-009-0043-1. [PubMed: 20098503]

Tian Y, Xiang X, Wu Y, Cao Y, Song J, Sun K, Liu H, and Hu Y. 2017 Fine Particulate Air Pollution and First Hospital Admissions for Ischemic Stroke in Beijing, China. Sci. Rep 7 (1): 3897. doi:10.1038/s41598-017-04312-5. [PubMed: 28634403]

Turpin BJ, Huntzicker JJ, and Hering SV. 1994 Investigation of Organic Aerosol Sampling Artifacts in the Los Angeles Basin. Atmos. Environ 28 (19): 3061–3071. doi:10.1016/1352-2310(94)00133-6.

Vaidyanathan A, Dimmick W, Kegler SR, and Qualters JR. 2013 Statistical Air Quality Predictions for Public Health Surveillance: Evaluation and Generation of County Level Metrics of PM2.5 for the Environmental Public Health Tracking Network. Int. J. Health Geogr 12 (1). BioMed Central: 12. doi:10.1186/1476-072X-12-12. [PubMed: 23497176]

Vaidyanathan A, Saha S, Vicedo-Cabrera AM, Gasparrini A, Abdurehman N, Jordan R, Hawkins M, Hess J, and Elixhauser A. 2019 Assessment of Extreme Heat and Hospitalizations to Inform Early Warning Systems. Proc. Natl. Acad. Sci. U. S. A 116 (12). National Academy of Sciences: 5420–5427. doi:10.1073/pnas.1806393116. [PubMed: 30833395]

Vaughan J, Lamb B, Frei C, Wilson R, Bowman C, Figueroa-Kaminsky C, Otterson S, et al. 2004 A Numerical Daily Air Quality Forecast System for the Pacific Northwest. Bull. Am. Meteorol. Soc 85 (4): 549–560. doi:10.1175/BAMS-85-4-549.

Wang J, and Christopher SA. 2003 Intercomparison between Satellite-Derived Aerosol Optical Thickness and PM 2.5 Mass: Implications for Air Quality Studies. Geophys. Res. Lett 30 (21): 2095. doi:10.1029/2003GL018174.

Wang Y, Hu X, Chang H, Waller L, Belle J, and Liu Y. 2018 A Bayesian Downscaler Model to Estimate Daily PM2.5 Levels in the Continental US, 8. doi:10.3390/ijerph15091999.

Weber SA, Insaf TZ, Hall ES, Talbot TO, and Huff AK. 2016 Assessing the Impact of Fine Particulate Matter (PM2.5) on Respiratory-Cardiovascular Chronic Diseases in the New York City Metropolitan Area Using Hierarchical Bayesian Model Estimates. Environ. Res 151 (11). Academic Press: 399–409. doi:10.1016/J.ENVRES.2016.07.012. [PubMed: 27543787]

Wettstein ZS, Hoshiko S, Fahimi J, Harrison RJ, Cascio WE, and Rappold AG. 2018 Cardiovascular and Cerebrovascular Emergency Department Visits Associated with Wildfire Smoke Exposure in California in 2015. J. Am. Heart Assoc 7 (8): e007492. doi:10.1161/JAHA.117.007492. [PubMed: 29643111]

Wilson WE, and Suh HH. 1997 Fine Particles and Coarse Particles: Concentration Relationships Relevant to Epidemiologic Studies. J. Air Waste Manag. Assoc 47 (12): 1238–49. http://www.ncbi.nlm.nih.gov/pubmed/9448515. [PubMed: 9448515]

Wu J-Z, Ge D-D, Zhou L-F, Hou L-Y, Zhou Y, and Li Q-Y. 2018 Effects of Particulate Matter on Allergic Respiratory Diseases. Chronic Dis. Transl. Med 4 (2): 95–102. doi:10.1016/j.cdtm.2018.04.001. [PubMed: 29988900]

Xiao Q, Zhang H, Choi M, Li S, Kondragunta S, Kim J, Holben B, Levy RC, and Liu Y. 2016 Evaluation of VIIRS, GOCI, and MODIS Collection 6 AOD Retrievals against Ground Sunphotometer Observations over East Asia. Atmos. Chem. Phys 16 (3): 1255–1269. doi:10.5194/acp-16-1255-2016.

Xu J-W, Martin RV, van Donkelaar A, Kim J, Choi M, Zhang Q, Geng G, et al. 2015 Estimating Ground-Level PM≪Sub≫2.5≪/Sub≫ in Eastern China Using Aerosol Optical Depth Determined from the GOCI Satellite Instrument. Atmos. Chem. Phys 15 (22): 13133–13144. doi:10.5194/acp-15-13133-2015.

Yang A, Janssen NAH, Brunekreef B, Cassee FR, Hoek G, and Gehring U. 2016 Children's Respiratory Health and Oxidative Potential of PM 2.5 : The PIAMA Birth Cohort Study. Occup. Environ. Med 73 (3): 154–160. doi:10.1136/oemed-2015-103175. [PubMed: 26755634]

Zeger SL, Thomas D, Dominici F, Samet JM, Schwartz J, Dockery D, and Cohen A. 2000 Exposure Measurement Error in Time-Series Studies of Air Pollution: Concepts and Consequences. Environ. Health Perspect 108 (5): 419–426. doi:10.1289/ehp.00108419. [PubMed: 10811568]

Zhai X, Russell AG, Sampath P, Mulholland JA, Kim B-U, Kim Y, and D'Onofrio D. 2016 Calibrating R-LINE Model Results with Observational Data to Develop Annual Mobile Source Air Pollutant Fields at Fine Spatial Resolution: Application in Atlanta. Atmos. Environ 147 (12). Pergamon: 446–457. doi:10.1016/J.ATMOSENV.2016.10.015.

Zhang G, Rui X, and Fan Y. 2018 Critical Review of Methods to Estimate PM2.5 Concentrations within Specified Research Region. ISPRS Int. J. Geo-Information 7 (9). Multidisciplinary Digital Publishing Institute: 368. doi:10.3390/ijgi7090368.

Zhang H, Hoff RM, and Engel-Cox JA. 2009 The Relation between Moderate Resolution Imaging Spectroradiometer (MODIS) Aerosol Optical Depth and PM 2.5 over the United States: A Geographical Comparison by U.S. Environmental Protection Agency Regions. J. Air Waste Manage. Assoc 59 (11): 1358–1369. doi:10.3155/1047-3289.59.11.1358.

Ziemba LD, Thornhill KL, Ferrare R, Barrick J, Beyersdorf AJ, Chen G, Crumeyrolle SN, et al. 2013 Airborne Observations of Aerosol Extinction by in Situ and Remote-Sensing Techniques: Evaluation of Particle Hygroscopicity. Geophys. Res. Lett 40 (2): 417–422. doi:10.1029/2012GL054428.

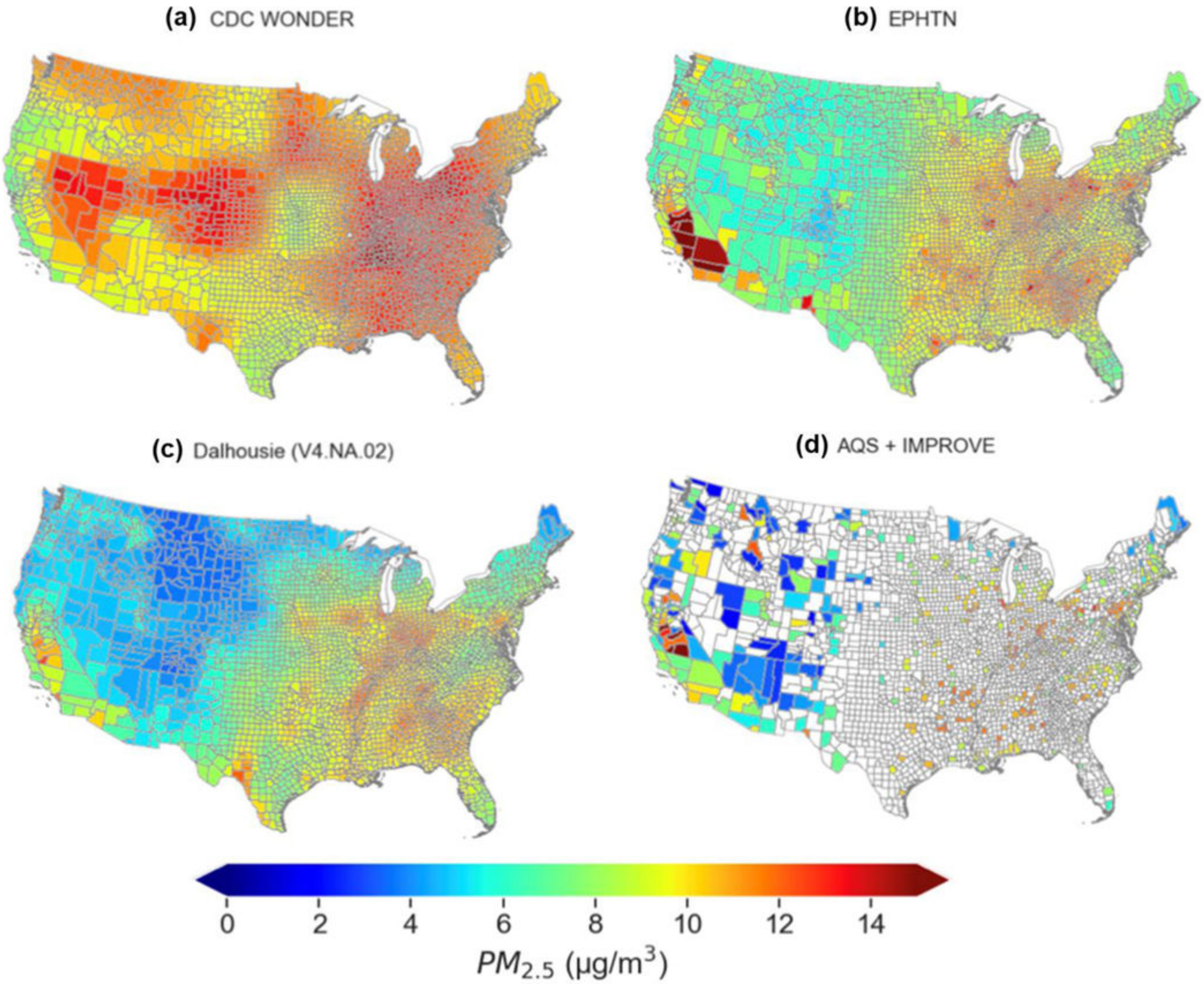

Figure 1.

County-level maps of annual mean $PM_{2.5}$ in 2011 using: (a) CDC WONDER, (b) EPHTN, (c) Dalhousie data (V4.NA.02), and (d) EPA AQS and IMPROVE fused data. White spots on the map represent "no data available".

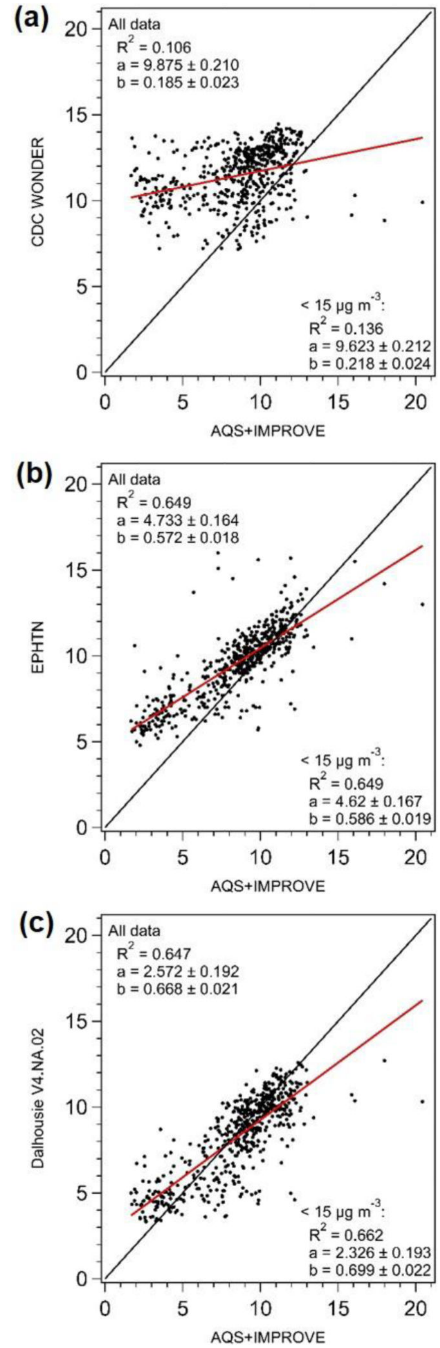

Figure 2.

Scatter plots of publicly available surface $PM_{2.5}$ datasets – (a) CDC WONDER, (b) EPHTN, and (c) Dalhousie (V4.NA.02) versus AQS+IMPROVE fused data. All data represent county-average 2011 annual mean. Two linear regressions are calculated: one for all data (top text box, red solid line showing this fit) and one for $PM_{2.5}$ < 15 μg m-3 only (bottom text box). Black solid line stands for 1:1 line. The value of a and b represent intercept and slope of the linear regression, respectively. The ±1σ stands for ± one standard deviation. The number of samples used for linear regression in (a), (b) and (c) are 543, 544 and 544, respectively.

EPA Author Manuscript

EPA Author Manuscript

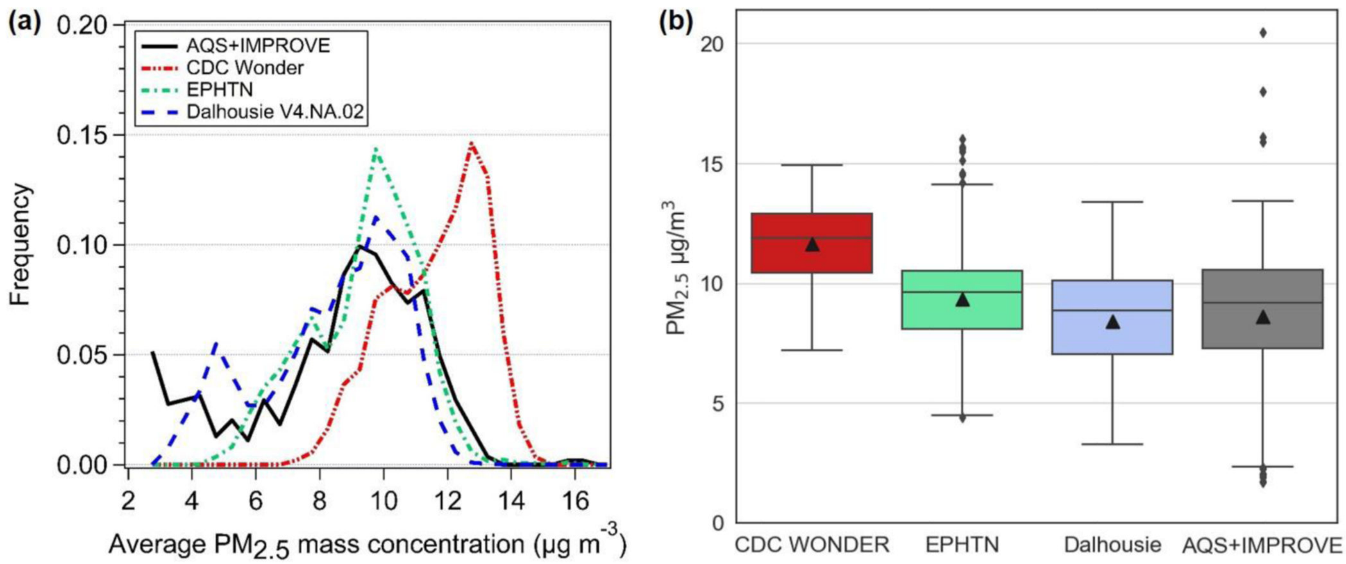

Figure 3.

(a) Frequency distributions of the county-average 2011 annual mean $PM_{2.5}$ mass concentrations for the four data sets shown in Figure 1. (b) Mean (triangles), median (horizontal bar in the middle), 25 and 75 percentiles (bottom and top of the box, respectively) for the four data sets. Black dots represent outliers.

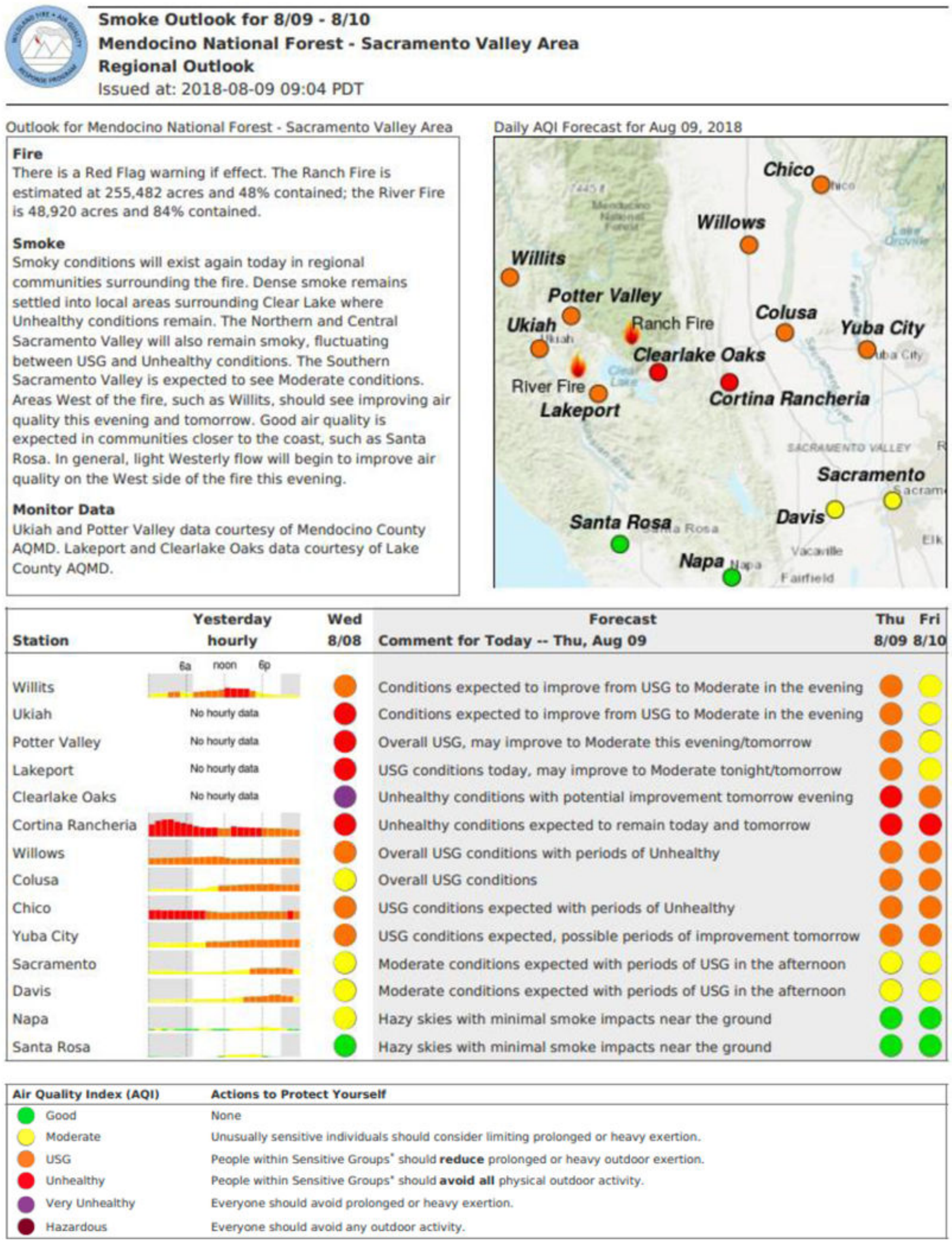

Figure 4.

An example of forecasting smoke conditions in local communities, using Smoke Outlook, for Ranch Fire and River Fire in Sacramento Valley area, California in August 9–10, 2018.

Table 1.

A summary of the publicly available $PM_{2.5}$ exposure datasets

	Source of Dataset	Region	Time Period	Spatial Resolution	Temporal Resolution	Monitor	Model	Satellite	Reference
1	GBD	Global	1990 – 2013	*0.1°× 0.1°	Annual	X	X	X	Brauer et al. (2016)
2	Dalhousie Dataset V4.GL.02	Global	1998 – 2016	1 km^2	Annual	X	X	X	*(1)*
3	GBD	Global	2014	*0.1°× 0.1°	Annual	X	X	X	Shaddick et al., (2018a)
4	Berkeley Earth	Global	2016 – 2017	*0.1°× 0.1°	Daily	X	X		*(2)*
5	Dalhousie Dataset V4.NA.02	CONUS	2000 – 2016	1 km^2	Annual	X	X	X	*(1)*
6	EPA AirData	CONUS	1999 – 2018	Point data; also available when averaged on county scale	Daily	X			*(3)*
7	EST 2013	CONUS	2001 – 2006	8.9 km^2	Monthly	X	X	X	Beckerman et al. (2013)
8	CDC EPHTN	CONUS	2001 – 2015	County and Census tract	Daily	X	X		*(4)*
9	EPA FAQSD	CONUS	2002 – 2015	12 km^2	Daily	X	X		*(5)*
10	CDC WONDER	CONUS	2003 – 2011	County	Daily	X		X	*(6)*
11	AQAH 2018	NC, USA	2006 – 2008	12 km^2	Monthly & Annual	X	X		Huang et al. (2018)

Table 1 shows spatially continuous $PM_{2.5}$ exposure datasets that are publicly available and free on individual websites or publications. The URLs of the datasets are listed below.

[*] At mid-latitudes, 1° is approximately 100 km.

(1). Dalhousie University Datasets: http://fizz.phys.dal.ca/~atmos/martin/?page_id=140

(2). Berkeley Earth Air Quality Map: http://berkeleyearth.org/air-quality-real-time-map/

(3). AirData Dataset: https://www.epa.gov/outdoor-air-quality-data/download-daily-data

(4). CDC EPHTN: https://ephtracking.cdc.gov/DataExplorer/#/

(5). EPA FAQSD Dataset: https://www.epa.gov/hesc/rsig-related-downloadable-data-files

(6). CDC WONDER: https://wonder.cdc.gov/nasa-pm.html

Table 2.

Summary of county-average 2011 annual mean $PM_{2.5}$ estimates of AQS+IMPROVE fused data, CDC WONDER, EPHTN and Dalhousie data in contiguous U.S.

$PM_{2.5}$ data	AQS+IMPROVE	CDC WONDER	EPHTN	Dalhousie
Minimum $PM_{2.5}$ value (μg/m^3)	1.7	7.2	4.4	3.3
Maximum $PM_{2.5}$ value (μg/m^3)	20.4	14.9	16.0	13.4
R^2 *		0.106 **	0.649	0.647
R^2 * for $PM_{2.5}$ < 15 μg m^{-3} only		0.136 **	0.649	0.662
Normalized mean bias *		33.3% **	12.2%	−3.3%
Number of samples used in analysis	544	3102	3104	3104

* R^2 and normalized mean bias are calculated based on county-mean to county-mean comparison with respect to AQS+IMPROVE data of 2011 annual mean.

** This is based on county-mean to county-mean comparison, but as for the grid-level validation, the surfacing algorithm that was used to create the CDC WONDER dataset was also validated on the grid level for the Southeastern US that showed an R^2 of 0.88 and RMSE of 1.6 μg/m^3 (Al-Hamdan et al., 2009).