Chapter 6: Surface monitoring of fire pollution

Allison E. Bredder[1]

[1] University of Maryland, Department of Geographical Sciences, USA

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1 Introduction

The impact of air quality (AQ) on health has been acknowledged by governments of individual countries and the World Health Organization (WHO) for more than half a century. The United States, the United Kingdom, and the Union of the Soviet Socialist Republics (USSR) were among the first to enact a version of a "Clean Air Act" around 1955-1956 aimed at controlling air pollution and minimizing negative impacts on public health (Barker et al., 1961). In 1958, the World Health Organization (WHO) published its first technical report – *Air pollution* – that explicitly linked exposure to high concentrations of pollutants to adverse health outcomes (World Health Organization, 1958). Although the report neither discussed the toxicology of individual pollutants nor proposed any guidelines on concentrations, it nonetheless was a major step towards the eventual development of national and subsequently global AQ standards.

Over time, many countries worldwide developed a set of rigorous science-based AQ standards, enacted laws and regulations, and established networks of monitoring stations. Reflecting the historical development of the AQ regulations, the monitoring stations are primarily focused on urban AQ with attention to populated areas (Ambient Air Quality Surveillance, 1994). In addition, considering that the primary purpose of these networks is to meet defined regulatory AQ goals from the regional to international levels, the expected accuracy of measurements and the precision of the instruments require careful cost consideration and make high-density spatial observations prohibitively expensive. While these traditional government-sponsored national air monitoring networks provide "gold standard" observations for a large suite of air pollutants, they are frequently far too sparse and suboptimally located to support monitoring of air pollution associated with biomass burning (Reid et al., 2015). Globally, biomass burning is highly varied (see Chapter 2).

New advancements and global proliferation of less costly air monitors, termed low-cost air quality sensors or LCAQS, has dramatically increased the potential for near-real-time monitoring of smoke events by governments, researchers, and citizen scientists alike. Although the advance of LCQAS has increased the availability of stationary measurements, their spatial patterns are frequently subject to similar limitations and biases towards urban environments but to a lesser degree.

This chapter provides a brief overview of the following topics:

1. An overview of AQ monitoring networks, including established regulatory networks, global and emerging networks, and LCAQS networks.
2. Common statistical methods to derive spatiotemporally resolved AQ estimates, with a focus on applications to particulate matter.
3. A discussion of the challenges associated with using AQ monitoring networks for smoke pollution monitoring.
4. The future directions and opportunities for monitoring smoke pollution.

2 Monitoring networks

Air quality monitoring networks, also referred to as surveillance networks, record information about levels of air pollutants (Marć et al., 2015). Monitoring networks measure a range of ambient air pollutants. The air pollutants that are most commonly collected include particulate matter that is less than or equal to 10 and 2.5 micrometers in aerodynamic diameter in size (known as PM_{10} and $PM_{2.5}$, respectively), ozone (O_3), mercury (Hg), sulfur dioxide (SO_2), nitrous oxides (NO_X), nitrous dioxide (NO_2), and persistent organic pollutants (Marć et al., 2015). Monitoring networks can be classified into two categories: regulatory (or reference) monitoring networks and LCAQS networks.

2.1 Regulatory AQ networks

Air pollution can contribute to a range of negative effects that impact humans, ecosystems, and man-made structures. Governments and regulatory bodies have a vested interest in monitoring AQ for economic, public health, and political reasons. Air quality monitoring systems operated by governments have increased since the 1800's, coinciding with air pollution impacts from the Industrial Revolution, and other large-scale air pollution events that resulted in negative impacts, such as the London Smog Event of 1952 that served as a catalyst for legislative change and investment in technology to monitor goals. Countries have adopted their own systems for monitoring AQ using ground-based monitors, with the responsibility for collecting and disseminating information typically assigned to entities broadly referred to as environmental protection agencies.

Regulatory monitors are broadly defined here as ground-based, stationary monitors (also known as *in situ* monitors) that are deployed by or on behalf of country-level governments. This section primarily focuses on regulatory networks to monitor AQ, defined as meeting two criteria: 1) the network is mandated or sponsored by or on behalf of a country's government, 2) the network is constructed of ground-based, stationary AQ monitors. Additionally, the focus is on networks where data are publicly available via the Internet, but other programmatic efforts are also discussed. They are typically used to meet legislative requirements such as ambient air quality standards or research purposes (Castell et al., 2017). However, with the proliferation of LCAQS, governments have also begun to invest in those to make information available in near real-time to support emergency management and to provide more information to communities interested in tracking smoke events (Morawska et al., 2018).

While not discussed here, there are dedicated efforts to assessing technology and methods associated with sampling AQ (Helsen, 2005; Shaddick & Zidek., 2014) and determining optimal locations where monitors should be located for optimal spatial distribution (Chapter 10) (Hao & Xie, 2018; Piersanti et al., 2015). Quantifying spatiotemporally resolved air pollution concentrations is critical for mapping biomass burning and understanding how biomass burning emissions are transported (Chapter 8).

Information about country-level AQ monitoring networks was derived from peer-reviewed and grey literature that described air AQ monitoring networks in the US by an English-speaker; therefore, a limitation for information provided in this section may be attributable to language or website accessibility from the US.

2.1.1 Established national AQ networks

Overall, as can be expected, most extensive networks and the longest archives of measurements are found within wealthy countries with a long history of industrial development. The world's older industrial giants (the US, UK, and USSR) were among the first to enact laws governing air pollution in the mid-20th century (Barker et al., 1961). These were rapidly joined by other industrialized countries, including many European countries, Canada (Government of Canada, 2021), and Japan (Wakamatsu et al., 2013), which initialized their national monitoring networks in the late 1960s – early 1970s. Over half of the century, these networks have undergone several major improvements, including the increase in number of measured pollutants, technical advances in instrumentation, improved statistical techniques, and substantial network growth.

In the US, the Environmental Protection Agency (EPA) is charged with collecting and disseminating AQ information from local, state, and tribal entities using Federal Reference Methods and Federal Equivalent Methods. The EPA monitoring network consists of over 4,000 stations that are distributed across all states and territories for criteria pollutants (CO, NO_2, O_3, Pb, PM_{10}, $PM_{2.5}$, and SO_2) and 188 other toxic air pollutants (US Environmental Protection Agency, 2021a). Data from the EPA monitoring cites are publicly available since 1980 for the criteria gases, 1988 for PM_{10} and 1999 for $PM_{2.5}$. Hazardous air pollutants and toxic air pollutants are available from 1980 (US Environmental Protection Agency, 2021d)). While these monitors are not specifically designed for biomass burning pollution, they are often used in studies focused on assessing the health effects of pollution from biomass burning (Chapter 10). These measurements are supplemented by over 90 Clean Air Status and Trends Network (CASTNet) deposition monitoring sites operated by EPA (US Environmental Protection Agency, 2021c) and the Interagency Monitoring of Protected Visual Environments (IMPROVE) network with 160 sites as of 2019 located in National Parks and in wilderness areas (Interagency Monitoring of Protected Visual Environments, 2020). In addition, the National Oceanographic and Atmospheric Administration (NOAA) Earth System Science Laboratory has measured surface ozone since 1973 at 20 sites across the world National Oceanic and Atmospheric Administration Global Monitoring Laboratory Earth System Research Laboratories, n.d.).

Like the EPA regulatory network across the US, Canada operates the National Air Pollution Surveillance (NAPS) program (Environment Canada, 2020), which aims to deliver consistent high-quality observations across the nation. At present, the NAPS boasts 286 sites in urban and rural communities across all provinces and territories. Although country-wide summaries have been published since 1972, these early reports are based on observations from a very small fraction of currently available sites. The NAPS program collects continuous and time-integrated measurements for a predetermined number of pollutants. Observations include CO, NO_2, NO, NO_X, O_3, SO_2, $PM_{2.5}$, and PM_{10}, with hourly and annual data are available for CO, SO_2, NO_2, and O_3 available since 1974. Particulate matter data is available since 1992 for PM_{10} and since 1995 for $PM_{2.5}$.

The European Environment Agency is responsible for establishing the policy framework for monitoring AQ across the EU zone (Directorate-General for Environment, n.d.). Through a series of directives, the EU established standards for ambient air concentrations for several pollutants, defines the methodologies for data collection, and monitors the compliance for each of the EU Member States. The Member States are expected to monitor and report AQ data by pre-defined zones and agglomerations (established by the Member States following the methodology defined by the agency), as well as make the AQ information available to the public through the European Air Quality Portal. At present, the number of operational stations totaled around 5,300 stations across the 41 contributing countries and territories (Air quality assessment methods (data flow D), 2020)).

In Australia, the National Clean Air Agreement establishes the framework for AQ monitoring (Commonwealth of Australia, 2015). Although Australia's urban areas are reported to have some of the best AQ in the world, biomass burning is widely acknowledged as a one of the primary sources or air pollution (Keywood et al., 2016). Similar to the EU framework, the National Environmental Protection Council administers legislation pertaining to AQ and provides scientific and policy support. Data collection, which follows pre-determined standards, called National Environment Protection Measures (NEPMs), is the responsibility of provincial and state governments who are also charged with managing AQ. While there was no centralized data repository found for all Australian data across all states, each jurisdiction offers varying levels of access to AQdata.

Although the USSR was the first country in the world to define the standards for acceptable AQ (Izmerov, 1974), the data from the government-sponsored monitoring network nor information about the precision of instruments, statistical methods, reporting frequency, or the number of monitoring sites does not appear to be publicly available. The Russian Federal Service for Hydrometeorology and Environmental Monitoring reports annually on the most polluted cities in Russia (Klyuev, 2019), which indicates the presence of the state-wide network of monitoring stations at least across major urban areas.

2.1.2 Global and emerging AQ networks

The global awareness of health impacts from AQ in urban areas was growing from the early 1970s, when the WHO published its technical report on air quality guidelines for urban areas (WHO Expert Committee on Air Quality Criteria and Guides for Urban Air Pollutants & World Health Organization, 1972), which included contributors from Egypt, India, and Japan in addition to the European and North American experts. However, AQ monitoring networks in much of the rest of the world have been relatively slow to grow. In Central, South America, the Caribbean, and Africa, the monitoring networks are sparse (Awokola et al., 2020; Riojas-Rodríguez et al., 2016). Riojas-Rodríguez et al. (2016) found in their review that only half (17 of 33) Latin American and Caribbean countries had AQ monitoring stations. There appears to be less consistency in collected measurements across the region, for example, PM_{10} measurements are collected in 104 cities while $PM_{2.5}$ measurements are collected only in 57 cities. According to Rees et al. (2019), only 13% (7 of 54 countries) in Africa provide reliable, real-time AQ monitoring; however, it is unclear if these are monitors meet the criteria of this section. Ghana, Nigeria, and Kenya each have 5 national level, manual stations (Gulia et al., 2020). South Africa is the only country in Africa with a monitoring network that was found to be available to the public. The network of 130 fully automated stations within the National Ambient Air Quality Monitoring Network (NAAQMN) of South Africa was launched in the late 2010s as a partnership between the Department of Environmental Affairs and the South African Weather Service (Gwaze & Mashele, 2018). In line with best practices from the international community, the agency monitors pollutants following established criteria and methodology and delivers the information to the public through a mobile application tool.

Air quality monitoring in Asia presents a unique set of challenges. On the one hand, expansive monitoring networks exist in some parts of Asia, with the other two largest government-run networks within Japan and South Korea. The Korean Ministry of Environment has provided real-time data at 16 locations since 2002 near the World Cup Stadium located in the capital city of Seoul and has provided public access to data in real-time since 2005 on a nationwide scale for CO, NO, SO_2, and $PM_{2.5}$ and 10 from 332 stations via the AirKorea website (Hwang et al., 2020). On the other hand, the two largest industrial economies of the continent – China and India – only comparatively recently launched their AQ monitoring networks. Although the China National Environmental Monitoring Center (CNEMC) was founded in 1980 by the Ministry of Ecology and Environment of China, AQ data has been collected only since 2013. The monitoring network has grown very rapidly to currently reach over 2,100 stations that monitor CO, NO_2, O_3, $PM_{2.5}$, PM_{10}, and SO_2 (China National Environmental Monitoring Centre, n.d.; Chu et al., 2021). The data are available via the CMEN website, , but the volume of observations is skewed towards eastern parts of the country. The Government of India initiated the National Clean Air Program (NCAP) only in the beginning of 2019 under the oversight of the Ministry of Environment, Forests and Climate Change (International Trade Administration, 2020). The network currently includes a suite of 703 manual monitoring stations and 134 Continuous Ambient Air Quality Monitoring Stations (CAAQMS – low-cost monitoring sensors), which is expected to grow substantially in the near future to the total of 1500 manual monitoring stations and an additional 150 CAAQMS (Sundaray, & Bhardwaj, 2019). In other parts of Asia, Vietnam has 29 fixed and mobile CAAQMs, Pakistan has 70 manual and CAAQMS, Bangladesh has 11 CAAQMS, Sri Lanka has 78 manual stations, Nepal and Bhutan have 12 and 3 CAAQMS, respectively (Gulia et al., 2020).

2.2 Low-cost air quality sensor (LCAQS) networks

Technological advances of the past decades combined with the growing public awareness of health consequences of environmental pollution globally have created a favorable climate for the development of alternative approaches to the regulatory AQ monitoring stations. Fueled by investment from commercial companies, governments, non-governmental organizations, and lay citizens, LCAQS networks have rapidly increased in number across the world. Considerably lower financial costs and expertise are required to set up and maintain these stations compared to regulatory-grade monitors, which has allowed for a manifold increase in surface measurements for a suite of pollutants (Table 1) deployed by government agencies and private citizens alike. LCAQS networks are attractive for use in biomass burning and prescribed fire smoke exposure assessment as they offer denser and more dispersed observations and are available worldwide, often in countries that do not have robust national monitoring networks. Although mobile LCAQS are available, they offer only episodic observations frequently associated with a particular event or project. In contrast, stationary LCAQS and monitoring networks – the focus of this chapter – provide consistent observations for a given location, similarly to those obtained by the regulatory networks.

The LCAQS networks contain several important components. First, the data is collected by low-cost technologies largely referenced as "sensors". The investment can range roughly between tens of dollars (for a single sensor) and $5,000 USD for more comprehensive kits (Feenstra et al., 2019; Holder et al., 2020; Rai et al., 2017). Adopting the definition from Rai et al. 2017, "low-cost sensors" refer to "anything costing less than the instrumentation cost required for demonstrating compliance with the air quality regulations" and can include single sensors or "sensing kits/nodes/platforms [that] typically include one or more sensors, microprocessor, data-logger, memory card, battery, and display" (Rai et al., 2017). . Monitoring networks are constructed of sensors and typically rely upon the internet of things, generally physical objects that are connected by the Internet (Xia et al., 2012), to disseminate access to the data collected by the sensors. For example, the PurpleAir LCAQS network collects data from Plantower PMS1003 sensors; the data collected from the sensors is made publicly available using a web map and an Application programming interface (API) for data download by end-users. The number of LCAQS networks are growing rapidly: the Fire and Smoke Map, OpenAQ, and Urban Air Action Platform, and the UN's Urban Air Action web platform help illustrate the potential capabilities of LCAQS for biomass burning AQ monitoring.

The US has piloted a web map called the Fire and Smoke Map (US Environmental Protection Agency, 2021b) that is targeted for biomass burning exposure assessment in North America (Figure 1). The web map integrates AQ and fire information from a variety of sources. Specifically, $PM_{2.5}$ concentrations are provided from permanent monitors, which feed into the AirNow network, and temporary $PM_{2.5}$ monitors, that are deployed by governmental agencies to monitor smoke events PurpleAir data - an increasingly popular network. For example, Gupta et al. (2018) used 180 PurpleAir $PM_{2.5}$ data in conjunction with satellite data to estimate $PM_{2.5}$ during California fires in 2017. The EPA led a nationwide effort of over 30 agencies at the state, local, and tribal levels to develop a nationwide correction for PurpleAir $PM_{2.5}$ measurements that are applied to the data displayed on the Fire and Smoke Map ("AirNow's Fire and Smoke Map", n.d.). Over 70 PurpleAir sensors were co-located with regulatory-grade monitors in the evaluation ("AirNow's Fire and Smoke Map", n.d.). Active fire detections from the National Oceanic and Atmospheric Administration's Hazard Mapping System (National Oceanic and Atmospheric Administration Office of Satellite and Product Operations National Environmental Satellite, Data and Information Service, n.d.) and large fire incidents from the US National Interagency Fire Center (InciWeb, n.d.) are also available as data layers on the web interface. The US AirNow Department of State network (US Department of State and US Environmental Protection Agency, n.d.) provides real-time $PM_{2.5}$ data from monitors on US embassies and consulates across the globe.

OpenAQ is an open-source platform that integrates reference-quality data from governments and low-cost AQ data from the Air Quality Data Commons, HabitMap, PurpleAir, and Carnegie Mellon University (OpenAQ, 2021). The platform primarily provides data regarding CO, NO_2, O_3, $PM_{2.5}$, PM_{10}, SO_2, and black carbon. The web platform provides download capability of two years of data (historic data can be retrieved from Amazon Web Services), an R wrapper, and a Python wrapper. The wrappers allow users to access the Application Programming Interface (OpenAQ, n.d.). Importantly, OpenAQ does not perform quality assessment of the data, which necessitates substantial effort in data cleaning and pre-processing when those datasets are acquired for research or management purposes.

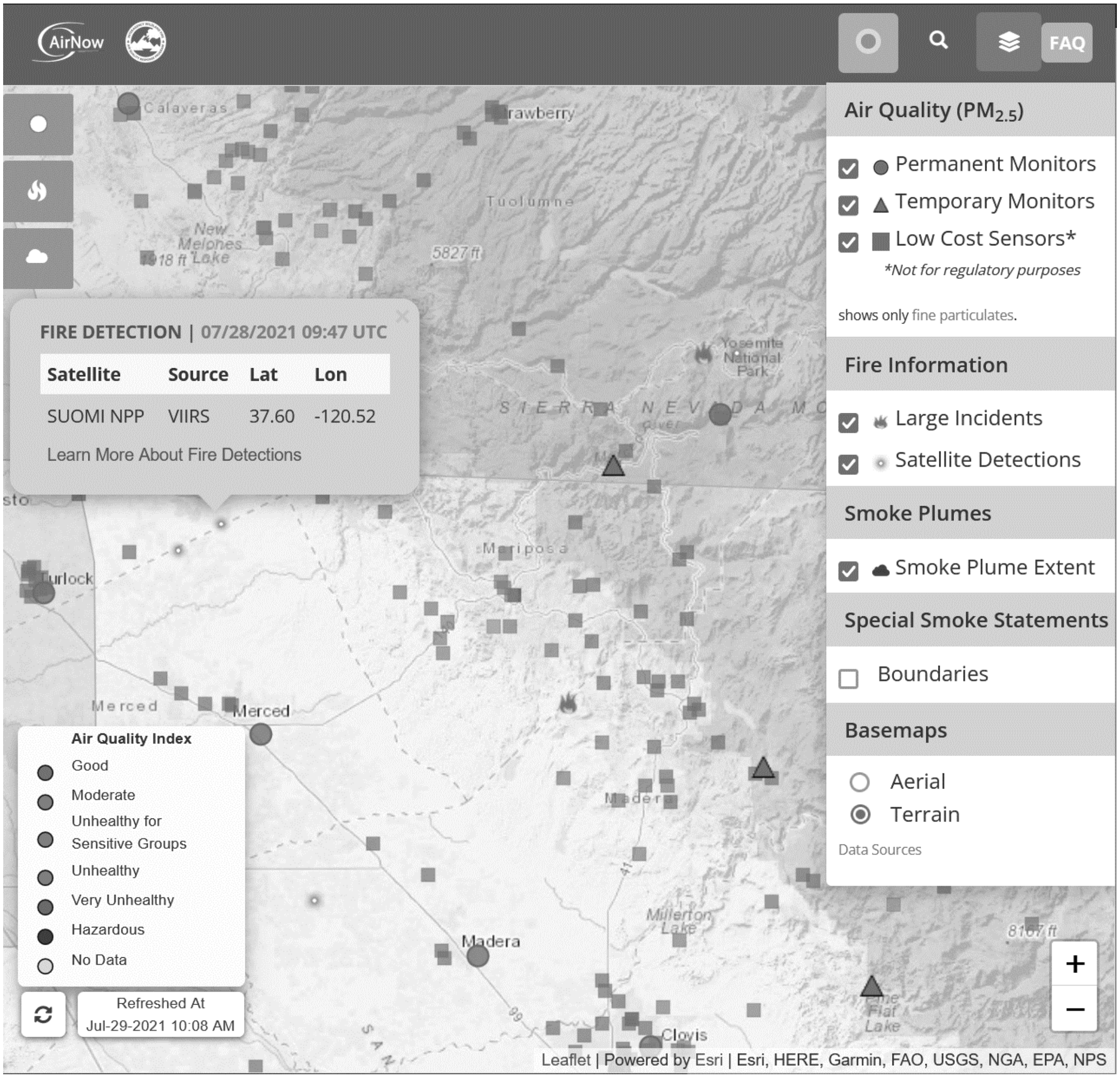

Figure 1. Screen capture of the Fire and Smoke Map web portal over California, US. Three types of air monitoring sensors are displayed with different shapes: squares represent PurpleAir sensors, triangles represent temporary sensors, and circles represent permanent stations. Each of the three types of air monitoring sensor is colored according to the Air Quality Index (legend shown) ("US Environmental Protection Agency", 2021a). Fire symbols large fires, and smaller circles represent active fires that are detected by satellites.

On a global scale, the United Nations (UN) Environment Programme and UN-Habitat deployed the Urban Air Action web platform in 2020 (United Nations Environment Programme, n.d.). The web platform displays near-real-time $PM_{2.5}$ data in collaboration with the commercial company IQAir, wind data, world population data, and fire locations.

Table 1. Selected low-cost air quality sensor (LCAQS) networks. Prices were retrieved in June 2021.

Network name	Pollutants measured	Sensor technology used and cost per individual sensor	Data retrieval location(s)
IQAir	• $PM_{2.5}$ • CO_2	• $269 (AirVisual Pro Air Quality Monitor)	Web map: United Nations Environment Programme, n.d
PurpleAir	• $PM_{0.3}$ • $PM_{0.5}$ • PM_1 • $PM_{2.5}$ • PM_5 • PM_{10} • PM_1 •	• $199 (PurpleAir PA-I-Indoor) • $249 (PurpleAir PA-II) • $279 (PurpleAir PA-II-SD)	Web map: PurpleAir, n.d. API: PurpleAir, 2021
Air Quality Egg	• CO, • CO_2, • NO_2, • O_3, • PM_1, • $PM_{2.5}$, • PM_{10}, • SO_2, • VOCs	• $130 (indoor) • $160 (outdoor)	Web map: Air Quality Egg, n.d.
AQICN	• $PM_{2.5}$ • PM_{10}	Aggregated from web sources	Web map: World Air Quality Index Project, 2022

3 Methods to estimate air pollution concentrations

Methods to develop spatially contiguous estimates of air pollution have rapidly evolved in the past nearly two decades with interest in using ground-based monitors and sensors for that exposure assessment in epidemiological studies (Chapter 7). Four categories of methods for developing continuous measurements will be discussed below, with particular attention to particulate matter: 1) spatial interpolation methods, 2) land use regression, 3) machine learning, and 4) chemical transport models (CTMs). Biomass burning events exhibit unique characteristics in space and time, and those unique characteristics can affect which modeling approach best represents smoke concentration and is feasible given model limitations (Mirzaei et al., 2018). Most of these approaches provide some measure of uncertainty. While statistical metrics are often reported to express error and uncertainty in interpolation, machine learning, regression, and chemical transport model efforts, it is common for only a sub-suite or the final chosen model to be presented and details regarding sensitivity analyses are absent (Gan et al., 2017; Hu et al., 2017; Stafoggia et al., 2019). Often, effect estimates due to model uncertainty are not reported for models that did not meet specified criteria, but this information could be useful for model selection in other applications (Arhami et al., 2013).

3.1 Spatial interpolation

Spatial interpolation involves using values with known locations to predict estimates where values are not known. For AQ applications, this frequently means using AQ monitor readings at one location to predict values where AQ readings do not exist, but can also be applied to raster data, such as satellite imagery. With the most simplistic spatial interpolation methods, no other ancillary data is required (Watson et al., 2019). Spatial interpolation methods are commonly used given the primary data input is known information and popular geostatistical and mapping software such as ArcGIS, QGIS and GRASS GIS, and R readily support spatial interpolation methods through functions and packages.

Thirty-eight spatial interpolation methods and sub-methods exist, with progress continuing to be made in this field (Li & Heap, 2014). These methods are commonly described and categorized according to dichotomies of features (Deligiorgi & Philippopoulos, 2011; Li & Heap, 2008; Li & Heap, 2014), including:

- Deterministic and stochastic methods: the primary difference between the two suites of methods is that deterministic methods do not incorporate randomness into their models while stochastic methods do. Thus, deterministic methods do not provide a measure of uncertainty, whereas stochastic methods provide error estimates.
- Global and local methods: global methods derive estimations using all data available in the study area whereas local methods use a sample of estimates in their calculation.
- Exact interpolators and approximate interpolators: exact interpolators derive values that are part of the known data whereas approximate interpolators can estimate values that are not the same as data that already exists.

To assist practitioners and researchers in determining which spatial interpolation method is best suited for the available information and desired results, Li & Heap (2014) provide a detailed decision tree that classifies spatial interpolation methods.

Two common spatial interpolation methods for wildfire AQ applications include inverse distance weighting (IDW) and kriging (Krige, 1951). Both methods realize Tobler's First Law: phenomena that are closer together in space are more like each other than to things that are located further away (Tobler, 1970). The IDW function interpolates values using existing values at a specified distance from the location without known values. Therefore, optimal application of IDW is when the known values are close in distance to unmeasured locations. Conversely, this method is less useful when predicting over areas where known values are farther away, such as remote rural areas where known values are sparse. Studies have used IDW to predict $PM_{2.5}$ using ground monitors (Wu et al., 2006; Yang et al., 2020). A large body of literature exists that is dedicated to developing new formulations for IDW (Ma et al., 2019).

Kriging also uses weights for closer values, but the weights also take into consideration the spatial patterns of known data. Currently, over 20 versions of kriging methods are in existence (Liu & Heap, 2014). As a geostatistical method, kriging delivers an uncertainty metric that can be useful to assess the performance of the algorithm. Kriging has been used to estimate $PM_{2.5}$ over Washington State, USA from reference-grade monitors (Gan et al., 2017) and over the coterminous USA and Ontario, Canada from 1988-2016 from research-grade monitors.

3.2 Statistical regression methods

Common statistical models to estimate pollutant concentrations include multiple linear regression, land-use regression, mix-effects modeling, generalized additive models (GAM), and geographically weighted regression (GWR). Earlier studies that used multiple linear regression to predict PM values established the importance of improving model estimations by including meteorological covariates (Chu et al., 2016). Land use regression (LUR), an extension of multiple linear regression, refers to regression models that are used to predict AQ concentrations (as the dependent variable), using covariates of ancillary information. However, despite what the name of this technique implies, the parameters are not always associated with land use (Watson et al., 2019). In practice, LUR models commonly incorporate meteorological information, including temperature, humidity, precipitation, wind, and air related variables, topographic variables, aerosol optical depth (AOD) (Chapter 7). For these methods, ground-level PM, ozone, or other pollutants are the dependent variable, and independent variables include AOD and other ancillary variables (Liu et al., 2005). Both multiple linear regression and land-use regression are limited in their effectiveness where covariates and ground-level PM have a non-linear relationship. Additionally, these approaches can become difficult to handle with large amounts of data (Hu et al., 2017; Shin et al., 2020).

Another extension of the multiple linear regression, the GAM, accounts for non-linear relationships between variables (Ma et al., 2014; Shin et al., 2020; Sorek-Hamer et al., 2013). The mix-effects modeling has largely replaced the use of MLR since 2010 (Chu et al., 2016). Fixed and random effects are incorporated into the mix-effects modeling to represent the background relationship between PM and AOD, and temporal and regional variation, respectively (Shin et al., 2020). Finally, geographically weighted regression accounts for non-stationarity and different relationships between ground-level and covariates (Luo et al., 2017; Shin et al., 2020). However, these models are highly sensitive to locations and distribution of ground stations (Shin et al., 2020) as well as the suite of ultimately selected variables. Considering that inclusion or exclusion of variables is subject to the discretion of the user, the resultant predictive capability is highly diverse as the tactics for selecting variables can vary widely among individual researchers and by discipline (Watson et al., 2019).
Using a linear regression model, Yao and Henderson (2014) estimated $PM_{2.5}$ concentrations in British Columbia in areas that did not have a monitoring network. They assessed model performance on low-, moderate-, and high-smoke days.

3.3 Machine learning

Machine learning refers to methods that use artificial intelligence which fit independent variables that are spatiotemporally variant (Watson et al., 2019). Machine learning approaches to estimate smoke concentrations have quickly become a dominant method in the past few years, as they do not assume linearity between the dependent variable and covariates and are stable and efficient for processing large amounts of data, increasing the capabilities for predicting longer

time series of trace gases and atmospheric pollutants (Bellinger et al., 2017). Popular machine learning techniques include kernel and tree-based approaches. Kernel-based approaches, such as support vector regression, are often used in multi-stage modeling (Shin et al., 2020; Song et al., 2014). Tree-based approaches rely upon decision trees to make predictions. These include classification/regression trees and random forest (RF) ensembles (Breiman, 2001), gradient boosting machines (Ferreira & Figueiredo, 2012), and extreme gradient boosting.
In 2015, Reid et al. compared eleven statistical models for predicting $PM_{2.5}$ during the 2008 biomass burning event in Northern California fires and found that the RF had among the highest cross-validated accuracy. Since this finding, machine learning algorithms, and specifically RF models, have been increasingly used to estimate the PM at regional and national scales (Chen et al., 2018a; Chen et al., 2018b; Di et al., 2019; Hu et al., 2017; Park et al., 2019; Reid et al., 2015; Stafoggia et al., 2019; Zhao et al., 2020). A more recent study showed a RF approach to predicting PM_{10} over China had better performance and improved predictive capabilities compared to traditional regression models (Chen et al., 2018b). In addition to predicting PM, machine learning has been used to predict other pollutants, including ozone exposure before and after biomass burning events (Watson et al., 2019). Cross-validation methods are common metrics to use to evaluate model performance and estimate uncertainty. A disadvantage of machine learning methods they often rely on specialized computer coding languages that are not always publicly available (Watson et al., 2019), although a number of open-source applications, including an R-package and a Python-based implementation, are openly available and easily accessible. In addition to the steep learning curve required to implement these methods, RF models are frequently referred to as “black box” methods, which implies that the internal algorithm decisions that produce the ultimate outcome are not always transparent, and it may be difficult to interpret the results (Affenzeller et al., 2020).

3.4 Chemical Transport Modeling

Chemical transport models rely upon meteorology, emissions inventories, and chemical and physical processes to quantify spatiotemporal patterns of atmospheric gases (Engel-Cox et al., 2013). Chemical transport models have been used to estimate PM and have been shown to be effective at coarser spatial resolutions and global scales. As CTMs do not rely upon ground-based measurements, these approaches are useful in areas where ground records do not exist or are highly heterogeneous (Boys et al., 2014; Chu et al., 2016; van Donkelaar et al., 2003). CTMs are more commonly used in multi-stage models for gap filling missing information, such as aerosol optical depth (Di et al., 2019; Stafoggia et al., 2019). Studies have also used CTMs to model biomass burning emissions on air pollution and to determine emission factors, (Akagi et al., 2011; Garcia-Menendez, Hu, & Odman et al., 2014; Hodzic et al., 2007; Konovalov et al., 2011; Wiedinmyer et al., 2006). A limitation of CTMs’ utility for biomass burning smoke is limited by knowledge of fire properties such as injection height and fuel loading (Paugam et al., 2016), meteorology uncertainties, and computational limitations to integrate the information into a useful model (Lassman et al., 2017). Chapter 8 provides a full review of CTM for biomass burning smoke concentration mapping.

4 Gaps and challenges in monitoring wildfire pollution

This chapter provides a selected overview of international AQ monitoring efforts based on information that is publicly available and accessible. Although these observations are undoubtedly a vital resource, comprehensive monitoring fire pollution using ground-based stations is unattainable because the task requires spatially and temporally inclusive estimates. Ultimately, the regulatory networks were never designed to monitor air pollution originating from biomass burning. Thus, they present a very limited, although valuable, source of information.

The technology that regulatory-grade monitors rely upon delivers highly accurate measurements at the point of data collection. However, the tradeoff is that the instruments are heavy, large, and expensive to construct and maintain. As a result, the spatial coverage of measurements from regulatory networks is very sparse. Fire events can be unpredictable in size, scale, and duration, making cost-effective instrumentation for effective monitoring extremely challenging. Considering the primary focus of regulatory networks on air pollution associated with industrial activity and transportation, monitors are typically found in urban centers. This positions the stations both away from the majority of ongoing biomass burning events. While stationary monitoring networks are established and continue to grow (Section 2) and temporary monitors are deployed during smoke events (Section 2.1), they deliver point measurement in 3-dimentional space and time. They also require a large subsequent effort to produce spatially contiguous estimates of AQ and pollutants' concentrations.

In addition to limited spatial coverage, conventional ground-based measurements represent measurements offer limited temporal coverage. Temporally, comprehensive AQ records rarely date back before the mid-20th century and are extremely limited in spatial coverage. Furthermore, some regulatory measurement sites record data every few days. This frequency may not be optimal to capture fire emission concentrations that are often short, episodic events. While there are benefits for collecting more data regarding ambient AQ, especially in unmonitored areas, there has been no concerted movement to increase the spatial resolution of reference monitors (Engel-Cox et al., 2013).

Despite government investment into using LCAQS to supplement regulatory data, there are still growing concerns that they are not able to replace reference measurements for regulatory decisions. While LCAQS offer advantages to supplement regulatory-grade information and empower more people to be engaged with monitoring AQ, the novelty of these sensors for regulatory purposes presents challenges. A primary known challenge is the quality of data reported by LCAQS. Previous studies have shown that data are subject to biases, and there are important considerations for obtaining high-quality data that is comparable to reference measurements (Giordano et al., 2021). A substantial effort has been focused on developing robust statistical approaches to calibrate data collected by LCAQS to those collected by instruments at the regulatory network stations (Barkjohn et al., 2021; Delp & Singer, 2020; Liu et al., 2017; Wallace et al., 2021). However, limited consensus has been reached in the literature regarding the best calibration, and it is likely regionally dependent upon other factors such as topography, meteorology, and other contributing factors. Assessing spatially contiguous AQ from regulatory and LCAQS networks presents an additional major challenge. Even in densely populated areas where many monitors may exist, there are no agreed-upon methods for extrapolating the stationary measurements to community and regional scales (Diao et al., 2019).

A key limitation of LCAQS is the lack of access to historical data. For example, web portals that integrate LCAQS information such as the Fire and Smoke map offer near-real-time information that is useful to track impact of on-going fire events. However, the tool has limited or no ability to download historic data. Therefore, these portals have very little utility in historic analysis or retrospective health studies that aim to study trends over longer time periods. Many sensors within LCAQS are owned and operated by lay citizens, which on the one hand diversifies the spatial distribution of sensors while on the other hand opens the door for potential measurement errors due to sensors that may have inaccurate location (e.g., wrong location provided to protect the owners' privacy), deployment, or maintenance of individual instruments (Barkjohn et al., 2021). Additionally, particularly for historical analysis, the global record of monitors is highly skewed towards high-income countries (The World Bank, 2021), limiting the utility for global analysis. Even in countries such as the US with a longer and denser network of AQ monitoring, the spatial resolution of reference monitors is generally too sparse to capture the behavior of smoke and provide decision-support information for managing decisions associated with exposure to biomass burning emissions (Reid et al., 2015; Sánchez-Balseca & Pérez, 2020; Watson et al., .

Key challenges exist for establishing and expanding AQ monitoring networks, especially at the global scale. For example, real-time AQ monitoring relies upon internet infrastructure and transportation infrastructure to support routine maintenance. In low and lower-middle-income (defined for fiscal year 2022 as countries that have gross national income per capita less than and between $1,046 and $4,095, respectively), both, and other reasons present challenges to these efforts (The World Bank Group, 2021).

5 Opportunities and future directions in monitoring wildfire pollution

The rapidly developing networks of LCAQS offer an exciting opportunity for delivering a more robust system of ground-based measurements valuable for smoke monitoring. Their potential is widely recognized by governments within developing and developed nations alike. And although outside the scope of this chapter, there is a large, growing body of literature that focuses on sensor technology, including calibration methods (Wallace et al., 2021) and performance compared to regulatory monitors during smoke events (Delp & Singer, 2020). With continuing development and improvements of cost-effectiveness among LCAQS and the improvements in the global satellites that enable web connectivity, it is reasonable to expect that LCAQS networks will become the leading component of global AQ monitoring system with an increased data availability in remote and sparsely populated regions where fire activity and smoke pollution are frequent and persistent. Open access to the observations from such a dense network will likely lead to substantial improvement in models delivering spatially and temporally resolved estimates of fire-related air pollution.

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