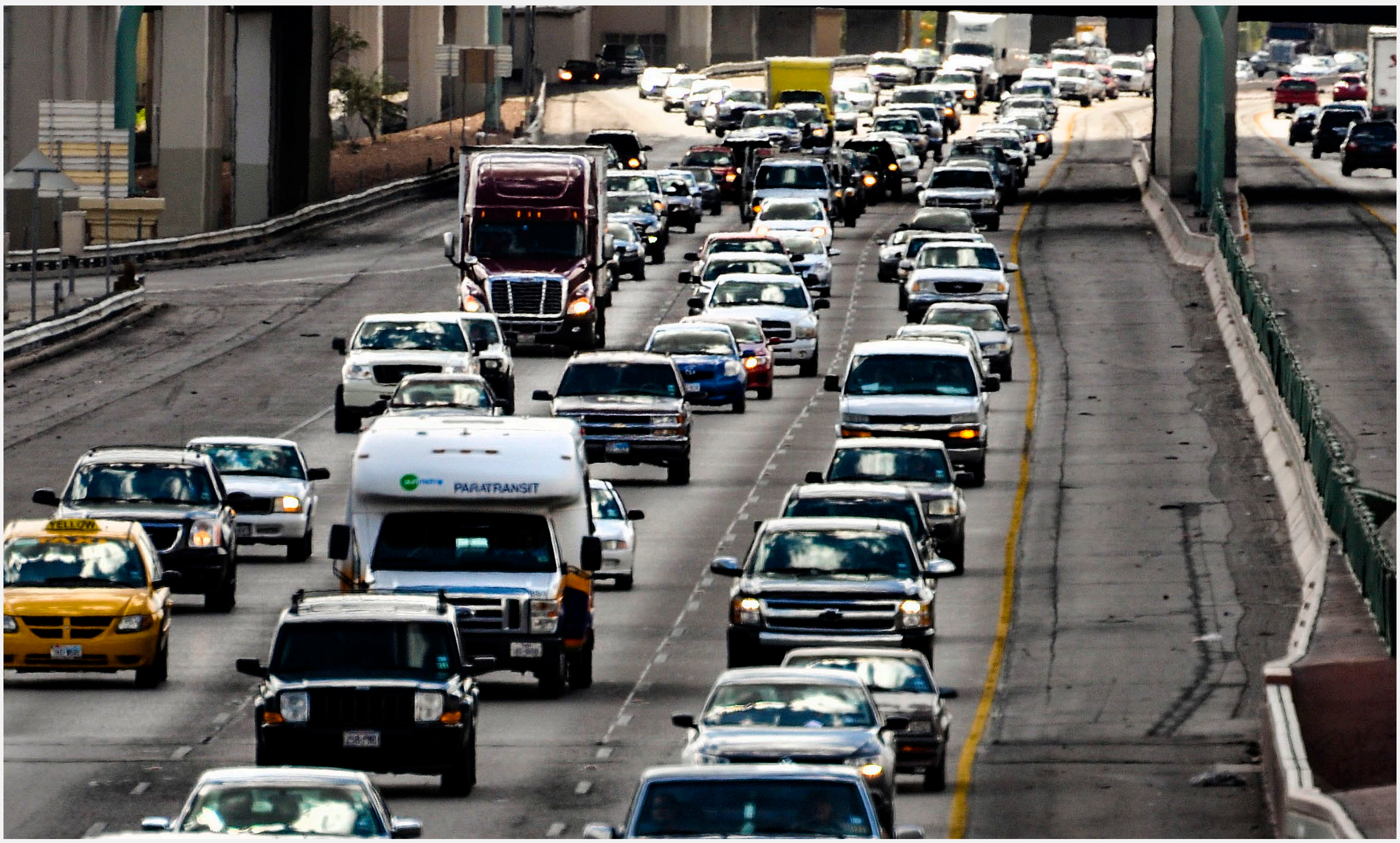
THE APPLICATION OF AIR QUALITY SENSORS FOR MONITORING AIR POLLUTION IN COMMUNITIES



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16. Abstract

Air pollution poses a significant threat to public health, with poor air quality linked to respiratory and cardiovascular diseases. Disadvantaged communities (DACs) are often disproportionately affected, leading to health disparities. Monitoring air quality is crucial to understanding these impacts and developing effective mitigation strategies. While traditional regulatory monitors provide important data, emerging air quality sensors (AQS) offer more localized information. This report examines the importance of monitoring air quality in communities, the categories and performance of AQS, and guidelines for selecting monitoring sites. DACs and Vulnerable Roadway Users (VRUs) experience higher exposure, emphasizing the need for equitable monitoring efforts. The use of AQS can enhance spatial resolution and community engagement. AQS categories include stationary, portable, and wearable sensors, each with unique advantages. While AQS accuracy varies, field testing and proper calibration are important. Guidelines for selecting monitoring sites include proximity to pollution sources, consideration of meteorological conditions, spatial coverage optimization, and equity concerns. The Environmental Protection Agency's *Enhanced Air Sensor Guidebook* can be referenced to aid in sensor selection and usage. Monitoring air quality and using AQS strategically can empower communities, drive policy changes, and contribute to healthier, more equitable environments.

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Executive Summary

Air pollution poses a significant threat to public health, with poor air quality linked to respiratory and cardiovascular diseases. Disadvantaged communities (DACs) are often disproportionately affected, leading to health disparities. Monitoring air quality is crucial to understanding these impacts and developing effective mitigation strategies. While traditional regulatory monitors provide important data, emerging air quality sensors (AQS) offer more localized information.

This report documents the importance of monitoring air quality in communities and the state of the practice of AQS, including discussion of the categories and performance of AQS and guidelines for selecting monitoring sites. DACs and vulnerable road users experience higher exposure to near-road traffic related air pollution (TRAP). This emphasizes the need for equitable monitoring efforts to ensure practitioners best understand the impacts of TRAP on the segments of our population that are most vulnerable.

The use of AQS can enhance spatial resolution and community engagement. AQS categories include stationary, portable, and wearable sensors, each with unique advantages. While AQS accuracy varies, field testing and proper calibration are important. Guidelines for selecting monitoring sites include proximity to pollution sources, consideration of meteorological conditions, spatial coverage optimization, and equity concerns. The Environmental Protection Agency's Enhanced Air Sensor Guidebook can be referenced to aid in sensor selection and usage. Monitoring air quality and using AQS strategically can empower communities, drive policy changes, and contribute to healthier, more equitable environments.

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Introduction

Air pollution is a widespread environmental issue that has detrimental impacts on public health. It is well-documented that poor air quality is highly correlated to respiratory and cardiovascular diseases (Jerret et al., 2005; Pope & Dockery, 2006; Kuzma et al., 2020). In addition, air pollution from traffic-related activities is a major concern in cities since the combustion of gasoline and diesel in vehicles emits harmful pollutants such as particulate matter (PM), nitrogen oxide (NO_x), and carbon monoxide (CO), which are associated with health risks (Jeyanthi et al., 2022).

Studies have also shown that there are disparities in the distribution of air pollution and health effects across communities. Certain communities and roadway users, particularly disadvantaged communities (DACs), are exposed to higher levels of air pollution and experience greater health burdens. Several factors influence the inequalities in air quality in these communities, including but not limited to proximity to major highways, socioeconomic status, race, access to resources, and environmental justice (Wilhelm & Ritz, 2009; Miranda et al., 2011; Jerret et al., 2013; Clark et al., 2014). There is an overrepresentation of non-white minorities and low-income individuals who reside in communities with poor air quality (Miranda et al., 2011; Clark et al., 2014), resulting in significant implications for public health (Wilhelm & Ritz, 2009, Jerret et al., 2013; Clark et al., 2014). This emphasizes the need to address air quality concerns in DACs to help improve health outcomes.

Improving air quality across communities is essential to enhance the overall well-being of populations and reduce health disparities. Efforts to reduce air pollution demonstrated a decrease in mortality rates and an improvement in respiratory and cardiovascular health (Jerrett et al., 2005; Miranda et al., 2011; Clark et al., 2014; Anderson et al., 2018; Kuzma et al., 2020). One study estimated that almost 7,000 deaths from heart disease can be prevented by reducing the concentration of NO_2 in DACs to levels that are experienced by non-DACs (Clark et al., 2014). Therefore, setting policies that mitigate air pollution can benefit populations at the community level. However, decision-makers should be cautious while implementing policies to ensure equitable air quality improvements in DACs (Anderson et al., 2018).

Air quality monitoring is of the utmost importance when it comes to understanding the extent of air pollution across communities. Deploying a network of air quality monitors can provide decision-makers and officials with the appropriate tools to identify areas with elevated levels of pollution. Consequently, it will be possible to implement targeted strategies that will reduce air pollution and protect public health (Anderson et al., 2018; Harcourt et al., 2018; Johnston et al., 2019). Additionally, proactively combining real-time monitoring systems and health surveillance will allow for a spatiotemporal assessment of air quality data and their associated health effects (Harcourt et al., 2018; Johnston et al., 2019). Moreover, inclusivity must be considered since all segments of the population should have access to ambient air quality information (Miranda et al, 2011).

Sensors are essential for the future of air quality monitoring. However, when selecting appropriate air quality sensors (AQS), users should consider the characteristics of the equipment to ensure accurate readings (Castell et al., 2017; Lewis et al., 2016). There have been massive improvements in spatial and temporal air quality data resolution due to innovative advancements in monitoring technology with the development of various types of AQS. In the past, government environmental agencies relied on sparsely distributed reference-grade instruments to collect air quality information. More recently, they started using a combination of both reference-grade and emerging monitoring technologies (Snyder et al., 2013). The United States Environmental Protection Agency (U.S. EPA) proposed a five-tier system for next-generation air monitoring, which included a wide range of AQS (U.S. EPA, 2013). The applications in each tier are related to specific demographics and projected users.

The primary objective of this report is to summarize existing literature, case studies, and examples on topics that can be categorized into the following sections:

- The importance of monitoring air quality in communities to help improve understanding of the impacts of air pollution on community health and well-being.
- Differentiate between reference or regulatory monitoring stations and other types of AQS available in the market.
- Guidelines and recommendations on the selection of appropriate locations for air quality monitoring in communities, with a focus on DACs.

Importance of Monitoring Air Quality in Communities

This section of the report will provide background information pertaining to key inquiries, such as the variability of air quality across communities. This inquiry will navigate air pollution concerns originating from traffic-related activities in neighborhoods. It will also examine the disproportionate impacts of air pollution that are experienced by certain population segments. Another inquiry that will be emphasized in this section is the significance of monitoring air quality within communities by examining equity considerations and environmental justice implications from monitoring initiatives. Moreover, the ramifications of policies and regulations to monitor air quality and reduce pollution in communities will be discussed as part of this inquiry.

Air Quality across Communities

The World Health Organization (WHO) estimated that almost 99 percent of the global population is exposed to unhealthy levels of air pollution, primarily NO_2 and PM, which exceed the WHO air quality standards (WHO, 2022). NO_2 is a common urban pollutant and is a precursor for PM (WHO, 2022). Both pollutants are products of human-related activities, mostly from the combustion of fuels in vehicles. Vehicular emissions contribute significantly to air pollution, and they are exacerbated in urban areas with high traffic congestion (Jeyanthi et al., 2022).

In recent decades, there has been a major need to address urban air pollution due to increasing traffic density and urbanization. Exposure to traffic-related air pollution (TRAP) is associated with a range of short- and long-term health effects, such as cardiovascular and respiratory diseases, increased inflammation, reduced cognitive functioning, and premature mortality (Pope & Dockery, 2006; Jerret et al., 2008; Tainio et al., 2016; WHO, 2022). According to a recent publication, the cognitive capabilities and performance of individuals can be negatively impacted by increases in PM concentrations in ambient air (Massachusetts Institute of Technology [MIT], 2023). Moreover, it is estimated that over 300,000 premature deaths can occur globally each year due to TRAP exposure (Anenberg et al., 2019). A key factor to consider concerning TRAP is the spatial resolution or the variation in concentration levels with distance from the roadway edge. The concentration of pollutants tends to be higher closer to the road, with the highest levels within the first 500 feet of a roadway. This is followed by a gradual decay in concentration toward background levels within approximately 2,000 feet of a roadway. Dispersion of pollutants depends on the pollutant type, time of day, and surrounding land use (Askariyeh et al., 2018).

Studies have acknowledged that certain segments of the population bear disparate burdens of poor air quality due to TRAP. DACs, often characterized by factors such as low income, high unemployment rates, racial and ethnic segregation, elevated housing and transportation expenses, limited transportation accessibility, and pronounced environmental stressors, have been identified as particularly vulnerable (Young et al., 2021). Individuals residing in low socioeconomic neighborhoods are frequently at a heightened risk of air pollution owing to their proximity to major roadways and the presence of heavy-duty freight traffic (Hajat et al., 2015). Consequently, DACs may experience more pronounced health complications resulting from higher pollutant concentrations (Wodtke et al., 2022). Alongside economic conditions, disparities in race and ethnicity are contributing factors. Ethnic minorities tend to be exposed to elevated levels of TRAP in contrast to White populations, both within the same geographical area and across varying income levels (Tessum et al., 2021). Other research studies have highlighted the equity dimensions within DACs in relation to transportation infrastructure. Despite having fewer car owners and a higher reliance on walking or public transit, individuals from low socioeconomic and minority groups tolerate a disproportional load of the impacts arising from TRAP (Pratt et al., 2015). The increased reliance on active modes of transportation by users in DACs exposes them to higher levels of air pollution (Lu et al., 2022). One significant opportunity for those living in DACs to protect themselves from TRAP-related health impacts is to have improved access to outdoor air quality levels in their localized environment to measure their individual-level exposures.

Importance of Monitoring Air Quality in Communities

Inequitable burdens of air pollution can be addressed effectively with rigorous air quality monitoring programs. Such programs will enable communities and agencies to collect extensive air quality data, identify pollution sources and hotspots, and identify pollution control measures (Pope and Dockery, 2006). Several studies highlighted the importance of monitoring air quality in neighborhoods:

- Spatial distribution: Factors such as the uneven distribution of polluting sources and dispersion mechanisms in urban settings can cause a wide variation in pollutant concentration over short distances (Apte et al., 2017). Therefore, relying on conventional regulatory monitoring stations to capture localized pollution hotspots becomes inadequate since they lack spatial resolution. As a result, monitoring air quality at a refined scale becomes essential to assess patterns and levels of pollution exposed by different communities (Apte et al., 2017).
- Equity and environmental justice concerns: DACs often lack access to reliable and up-to-date air quality information, which prevents them from determining concentration levels in their area and impacts their ability to make informed health decisions (Miranda et al., 2011). The absence of monitoring data will consequently aggravate the existing environmental injustices encountered by these communities (Lu et al., 2022). This underscores the need to develop community-based air quality monitoring programs.
- Policy and planning: Identifying locations with high air pollution concentrations will require extensive air quality data. Monitoring ambient air will provide urban planners and decision-makers with essential information to develop policies and guide the implementation of targeted intervention strategies to improve air quality (Anderson et al., 2018). Therefore, ensuring the creation of healthier and more sustainable communities (Sallis et al., 2009). Furthermore, evaluating the effectiveness of policies based on the needs of each community can result in equitable outcomes from the air pollution reduction measures (Anderson et al., 2018).
- Community engagement: Recent studies have demonstrated that monitoring air quality in neighborhoods, especially DACs, can potentially strengthen community engagement (Commodore et al., 2017). Residents will be empowered to actively participate in decision-making processes to help them understand local air quality concerns and identify feasible solutions (Commodore et al., 2017; Ward et al., 2022). Developing community-based air quality monitoring programs can improve awareness among residents and advocate for their rights to clean air (Ilie et al., 2022). These programs will also promote collaboration between community members, planners, and policymakers to develop location-specific air pollution reduction strategies.

Regulatory Reference Stations vs. Air Quality Sensors

Following the discussion underlining the significance of promoting monitoring efforts aimed at addressing equity concerns and enhancing accessibility to clean air in communities, this section will examine the following themes. Firstly, current practices for monitoring air quality in neighborhoods will be explored. This includes an inquiry into the limitations related to these monitoring techniques. The second inquiry will explore the role of emerging air quality sensing technology in addressing concerns stemming from current monitoring practices. This will include an identification/categorization of widely accessible AQS and an evaluation of how these new sensors stand in comparison to regulatory stations.

Recent changes in the realm of air pollution monitoring (Snyder et al., 2013) have created opportunities for communities to have direct access to air quality data. Traditionally, pollutant concentrations are measured by ambient monitoring stations established by EPA for regulatory compliance and to determine region-wide exposure. This is a direct result of the Clean Air Act (U.S. EPA, 2022a) that requires states to establish a network of regulatory or reference monitors to monitor criteria air pollutants, which include PM, ozone (O_3), CO, sulfur dioxide (SO_2), nitrogen dioxide (NO_2), and lead (Pb). However, regulatory monitors are limited by spatial coverage and do not provide source- or time-specific contributions. Additionally, the placement of these monitors—usually around 10 feet above the ground—does not reflect the true pollutant exposure at an individual level (Mihăiță et al., 2019). Although reference monitors are more accurate, can detect more pollutants, and have longer operating lifetimes; they are expensive to maintain and require highly trained technical staff to operate.

Over the past several years, there has been a shift towards utilizing air quality sensing technology, which allows individuals to access air-quality data in their localized environment (Snyder et al., 2013). Unlike reference monitors, AQS are lower in price and require minimal training to operate. AQS can be divided into two main types: PM sensors and gaseous sensors. Current studies indicate that more information has been published on the use of PM sensors, rather than gaseous sensors that detect O_3, NO_2, CO, and other pollutants (McKercher et al., 2017). Within this classification, there are additional subtypes of sensors depending on their specific detection methods (Concas et al., 2021; Snyder et al., 2013). Therefore, choosing between sensor technologies depends on the deployment characteristics and overall goals of the study.

Particulate matter sensors typically work by light-scattering techniques, where a light beam is scanned across aerosols in the airflow. These sensors can be further divided into volume-scattering devices and optical particle counts. For PM sensors, the most prominent sensor technologies include:

- Optical particle detectors: measure light scattering particles to estimate the number of particles in the air.
- Diffusion size classifiers: separate between different particle sizes by applying electrical signals to charge the air passing through the sensor.

While PM sensors utilize certain properties of a sensing material, such as electrical conductivity, capacitance, or mass, the function of gaseous sensors involves monitoring those qualities as they change with exposure to the gas species (Comini et al., 2009; Kalantar-Zadeh and Fry, 2008; Lui et al., 2012). For AQS that analyze gaseous pollutants, there are additional categories of sensing technologies with different characteristics:

- Metal oxide sensors: detect gases through chemical reactions occurring on the surface of the sensor.
- Electrochemical sensors: detect gases by oxidation-reduction reactions.
- Photoionization sensors: ionize volatile organic compounds and measure the resulting electric current.
- Optical sensors: detect gases by measuring the absorption of infrared light.

Importance of Using Air Quality Sensors

Region-wide concentrations of pollutants are determined using mechanistic air quality models (Tessum et al., 2017). However, the accuracy of these models is constrained at the microscopic level due to assumptions made about the toxicity of pollutants and variability of emissions from various sources (Lelieveld et al., 2015). Therefore, the availability of AQS significantly increases access to air quality monitoring data and provides a more comprehensive analysis of air pollution hotspots, specifically in areas without traditional monitoring stations (Castell, et al., 2017; Ionascu et al., 2018; Khreis et al., 2022; Kumar et al., 2015). Currently, there is an uneven network of fixed regulatory monitors across communities resulting in an incomplete picture of air pollution levels. Air pollution exposure levels vary widely within cities based on factors such as proximity to major roadways and the overall design of the built environment. Therefore, fixed stations can result in several gaps in air pollution spatial data. Even though these new sensors are typically less accurate than regulatory monitors, improvements in spatial and temporal data resolution have advanced the development of AQS technology. To that end, AQS offers an enhanced understanding of where individuals are most frequently impacted by TRAP (McKercher and Vanos, 2017). However, even with the technological advancements, these sensors are still not as widely used in urban environments, where air quality levels are typically worse. More work is needed to encourage the widespread adoption of these technologies to better understand air pollution exposures (Kumar et al., 2015). Moreover, studies have identified the need to develop better personal air pollution monitoring systems and mobile applications with wireless connections that utilize GPS data (Borghi et al., 2017; McKercher et al., 2017). This will provide users with the opportunity to receive more personalized air pollution exposure information.

A new air quality monitoring report from C40 highlighted the crucial role of AQS by providing insights from pilot studies that deployed sensor networks in different global cities (Oladini et al., 2022). The intent of these pilot studies is to help decision-makers gain a better understanding of the health issues associated with air pollution and expand public awareness while building evidence on the risk of air pollution. Moreover, air pollution exposure levels can be evaluated to address environmental inequities. Cities will also have increased access to city-scale data to help them solve urban air quality problems more efficiently and effectively. Some of the notable examples include:

- Addis Ababa, Ethiopia: They are interested in rapidly growing the number of air quality sensors to collect better data for informed decisions.
- Dar Es Salaam, Tanzania: The city council wants to understand basic information on pollution levels across the city.
- Denver, Colorado, USA: Deploying sensors in public school campuses to educate, encourage, and protect schoolchildren.
- Lima, Peru: Protecting the health of vulnerable populations, particularly young children, is a priority for the city. They are trying to understand the risk of air pollution on the health of children.
- Lisbon, Portugal: The city has a vision to achieve zero emissions and create a healthier environment. They plan to achieve this goal by increasing spatial coverage of real-time air quality monitoring.
- London, United Kingdom: Through community engagement, the city is encouraging residents to host sensors to build an extensive monitoring network.
- Los Angeles, California, USA: Sensors will be installed near parks and schools to monitor air quality in disadvantaged communities.
- Mumbai, India: They are testing the deployment of AQS at a city scale with plans for national adoption.
- Paris, France: The pilot study deployed sensors in schools to better understand air quality.
- Quezon City, China: The city is collecting baseline air quality data to identify air pollution hotspots, which can lead to more localized mitigation strategies.

Categories of Air Quality Sensors Based on Applicability

There are various applications for AQS, such as placing them at fixed locations or using them for personal exposure assessments (Liu et al., 2020). Categorizing monitoring devices by use and technology can be beneficial to users (McKercher et al., 2017). Since many of the current AQS in the market vary widely in design, functionality, and convenience, dividing them into categories presents an opportunity to expand research and development.

Based on published literature regarding the current state of AQS technology applications in real-world scenarios, this report will introduce three viable categories of AQS when applied in real-world scenarios:

- Stationary air quality sensors.
- Personal portable air quality sensors.
- Personal wearable air quality sensors.

Characteristics that determine how to distinguish between sensor types include price, weight, size, ease of use, and accessibility of data. Stationary AQS include those that are too large to be carried or worn by the individual user and instead operate as fixed and/or mounted monitoring stations. Personal portable AQS can be mounted on a bicycle or carried in a backpack, while personal wearable AQS can be worn by the user—such as on the wrist, around the neck, or attached to a belt loop—as a convenient alternative. Preferably, the personal wearable category consists of the most user-friendly sensors with easily accessible data through mobile wireless or USB connections. If marketed at reasonable prices, these sensors can be deployed to community members to track their personal daily exposures.

One important consideration prior to the widespread application of AQS is understanding the willingness of consumers and stakeholders to adopt them. A study by Sakhnini et al. (2020) found that although 90 percent of the participants expressed their concerns about the adverse impacts of air pollution, only 10 percent regularly monitor their exposure. Additionally, participants who are likely to use a portable AQS prefer to attach a wearable device to their bags rather than carrying it around their waist or neck. Hence, there is a need to design sensing devices that cater to the needs of consumers. Duncan et al. (2008) emphasized that continuous feedback from AQS users is crucial to improve the usability of these devices and monitor pollutant exposure more effectively. There is also a lack of understanding about how individuals and communities effectively use sensing technology (McKercher et al., 2017; Sakhnini et al., 2020).

Documentation of Air Quality Sensors in the Market

Currently, there is a lack of accessible information on the performance of various AQS, which makes it difficult to select the best sensor for monitoring purposes (Karagulian et al., 2019). This report will provide a functional resource to analyze commercially available AQS in the market. PM and gaseous sensors that met certain criteria, such as a high R^2 value or having been tested by trusted third parties, are listed in Table 1 and Table 2, respectively. The mean field R^2 value was used as a determining factor to include sensors in the lists. The R^2 value expresses the strength of the relationship between the average sensor measurements in comparison to the corresponding reference monitor measurements (Polidori et al., 2017). Several studies analyzed the effectiveness of various sensors; however, it is challenging to compare between studies due to the substantial range of results. A report by EPA reviewed numerous AQS studies and found that their performance varied widely, with reported R^2 values ranging from 0.07 to 0.91 (U.S. EPA, 2018). Sensors with a mean field R^2 of at least 0.70 were considered in this report since this has been found to demonstrate a robust agreement (Kang et al., 2022; Karagulian et al., 2019; Moore et al., 2015).

To minimize the variations in results and allow for more appropriate comparisons among AQS, this report will only focus on sensors that were tested by the Air Quality Sensor Performance Evaluation Center (AQ-SPEC), a center within the South Coast Air Quality Management District (SCAQMD, 2022), as well as field evaluations conducted by EPA (Williams et al., 2014). The AQ-SPEC program evaluates various AQS under both field and laboratory conditions to inform the public about their performance. To be tested by SCAQMD, each sensor must meet specific selection criteria, such as being able to detect one of the criteria air pollutants identified by EPA, and providing real- or near-real-time measurements, among others.

For each documented sensor, the following information regarding different domains are summarized in the tables:

- Category: stationary, personal portable, or personal wearable.
- Pollutant type: CO, NO, NO_2, O_3, SO_2, PM_1, $PM_{2.5}$ or PM_{10}.
- Average field R^2.
- Field mean absolute error (MAE).
- Sensing mechanism.

- Time resolution (minutes).
- Indoor or outdoor use.

Evaluating the Performance of Air Quality Sensors

Overall, there is variation in the evidentiary support regarding the application of AQS to evaluate air pollution exposure. Some studies demonstrated high efficacy, while others indicated many weaknesses that must still be addressed (Kumar et al., 2015). The main drawbacks of AQS include their limited accuracy and sensitivity, low stability, short lifespan, and sometimes tedious calibration process (Concas et al., 2021; Ionascu et al., 2018). Additionally, sensors can be heavily influenced by weather and environmental conditions—including temperature, wind, humidity, shock, and vibrations—as well as pollutant composition and particle size (Wang et al., 2015). Another challenge is integrating data from different monitoring sources and ensuring data standardization (Yi et al., 2015). Harmonizing data from various monitoring platforms is important for accurate and reliable air quality assessments. Finally, many studies have raised concerns regarding the unknown data quality of AQS. There is a lack of recommendations or solutions to comprehensively address this issue (Kang et al., 2022).

Determining the effectiveness of AQS in real-world applications requires field studies since laboratory performance inadequately predicts field performance (Castell et al., 2017). Feinberg et al. (2018) demonstrated that the performance of AQS is lower in the field compared to lab assessments, which is attributable to differences in response factors. Researchers also suggest testing AQS against regulatory monitors in different field locations with varying pollutant concentrations to maximize the performance of the sensors (Jiao et al., 2016). Continued field testing is recommended to comprehensively understand the mechanism of the evolving sensor technologies (Feinberg et al., 2018).

Many studies have also demonstrated that the accuracy of results obtained from AQS readings is highly dependent on proper calibration techniques (Manikonda et al., 2016; Sousan et al., 2017; Liu et al., 2017). It is essential that users regularly calibrate the sensors once they are installed to ensure consistent and reliable results (Khreis et al., 2022). It is recommended to calibrate sensors in real-world conditions to allow for transferability of results. In general, the linear model and the multi-linear regression model are the most used methods of calibration (Karagulian et al., 2019). Conversely, laboratory calibration often struggles to account for real-world environmental conditions (Castell et al., 2017). Potential solutions to minimize inconsistent results due to calibration include auto-calibration, periodic re-calibration, or machine learning–based calibration (Concas et al., 2021; Ionascu et al., 2018).

Table 1. Documented Particulate Matter Sensors

Sensor Model	Category	Pollutant Type	Field R^2	Field MAE*	Sensing Mechanism	Time Resolution	Indoor or Outdoor
Aeroqual (AQY-R)	Stationary	PM2.5	0.74	2.9 to 5.1	Laser Particle Counter	1 minute	Outdoor
Aeroqual (AQY v1.0)	Stationary	PM2.5	0.79	4.2 to 5.3	Laser Particle Counter	1 minute	Outdoor
Aeroqual (S500-PM)	Portable	PM2.5	0.96	N/A	Laser Particle Counter	5 minutes	Indoor and Outdoor
Airly	Stationary	PM1.0	0.84	4.2 to 5.3	Laser Particle Counter	5 minutes	Indoor and Outdoor
		PM2.5	0.86	4.5 to 5.0			
Air Quality Egg (2018 model)	Stationary	PM1.0	0.87	2.1 to 2.3	Optical Particle Counter	1 minute	Indoor and Outdoor
		PM2.5	0.85	4.4 to 5.3			
		PM1.0	0.87	N/A			
Air Quality Egg (Version 2)	Stationary	PM2.5	0.82	N/A	Optical Particle Counter	1 minute	Indoor and Outdoor
Air Quality Egg (2022 model)	Portable	PM1.0	0.87	2.9 to 3.9	Optical Particle Counter	1 minute	Indoor and Outdoor
		PM2.5	0.89	6.0 to 7.1			
Alphasense (OPC-N2)	Stationary	PM1.0	0.73	N/A	Optical Particle Counter	0.25 minutes	Indoor and Outdoor
		PM2.5	0.73	N/A			
Alphasense (OPC-N3)	Stationary	PM1.0	0.80	4.4 to 5.0	Optical Particle Counter	0.17 minutes	Indoor and Outdoor
Alphasense (OPC-R2)	Portable	PM1.0	0.82	7.8 to 11.8	Optical Particle Counter	0.5 minutes	Indoor and Outdoor
		PM2.5	0.73	7.3 to 10.0			
		PM10	0.78	7.8 to 15.4			
Applied Particle Technology (MINIMA)	Wearable	PM1.0	0.87	5.0 to 5.6	Optical Particle Counter	0.25 minutes	Indoor and Outdoor
		PM2.5	0.88	5.8 to 6.5			
AS-LUNG (Air Quality Station)	Stationary	PM1.0	0.88	N/A	Optical Particle Counter	0.25 minutes	Indoor and Outdoor
		PM2.5	0.70	8.0 to 12.1			
AS-LUNG (Portable)	Portable	PM1.0	0.86	3.2 to 4.3	Optical Particle Counter	0.25 minutes	Indoor and Outdoor
		PM2.5	0.78	6.8 to 8.2			
		PM1.0	0.89	N/A			
Atmotube (Pro)	Wearable	PM1.0	0.92	3.6 to 4.6	Optical Particle Counter	1 minute	Indoor and Outdoor
		PM2.5	0.88	4.9 to 5.9			
Blues Wireless (Airnote)	Stationary	PM1.0	0.77	4.3 to 6.8	Optical Particle Counter	1 minute	Outdoor
		PM2.5	0.71	4.4 to 7.1			
Clarity (Node)	Stationary	PM2.5	0.75	3.0 to 3.4	Optical Particle Counter	2–4 minutes	Outdoor
Davis Instruments (Airlink)	Stationary	PM1.0	0.87	2.2 to 2.8	Optical Particle Counter	1 minute	Indoor and Outdoor
		PM2.5	0.78	4.9 to 5.9			
Dylos (DC1100 Pro)	Stationary	PM2.5	0.75	4.2	Optical Particle Counter	1 minute	Indoor and Outdoor
Edimax (AirBox)	Stationary	PM2.5	0.74	4.4 to 5.5	Optical Particle Counter	~6 minutes	Outdoor
Elitech (Temtop LKC-1000S+)	Portable	PM2.5	0.92	3.1 to 3.6	Optical Particle Counter	1 minute	Indoor and Outdoor
Elitech (Temtop M2000 2nd Gen)	Portable	PM2.5	0.8	2.1 to 3.2	Optical Particle Counter	1 minute	Indoor and Outdoor

Table 1 (Continued). Documented Particulate Matter Sensors

Sensor Model	Category	Pollutant Type	Field R^2	Field MAE*	Sensing Mechanism	Time Resolution	Indoor or Outdoor
Elitech (Temtop PMD 351)	Portable	PM1.0	0.72	2.4 to 3.8	Optical Particle Counter	1 minute	Indoor and Outdoor
		PM2.5	0.73	3.8 to 5.8			
FabLab (Smart Citizen Kit V2.1)	Stationary	PM1.0	0.94	2.9 to 3.0	Optical Particle Counter	1 minute	Outdoor
		PM2.5	0.77	8.3 to 10.7			
HabitatMap (AirBeam2)	Wearable	PM2.5	0.69	3.3 to 3.7	Optical Particle Counter	1 minute	Outdoor
HabitatMap (AirBeam3)	Wearable	PM1.0	0.96	1.3 to 2.6	Optical Particle Counter	1 minute	Outdoor
		PM2.5	0.85	3.6 to 5.3			
Kunak (Air A10)	Stationary	PM2.5	0.72	5.4 to 6.4	Optical Particle Counter	5 minutes	Outdoor
Liveable Cities (SLX-PM2.5)	Stationary	PM2.5	0.81	6.4 to 9.1	Optical Particle Counter	1 minute	Outdoor
		PM10	0.74	11.9 to 18.1			
Lunar Outpost (Canary-S)	Stationary	PM2.5	0.83	3.3 to 3.8	Optical Particle Counter	1 minute	Outdoor
Magnasci SRL (uRADMonitor A3 HW105)	Stationary	PM1.0	0.83	4.0 to 5.2	Optical Particle Counter	1–9 minutes	Indoor and Outdoor
		PM2.5	0.77	5.2 to 8.9			
Magnasci SRL (uRADMonitor INDUSTRIAL HW103)	Stationary	PM1.0	0.79	2.7 to 3.7	Optical Particle Counter	1–5 minutes	Indoor and Outdoor
		PM2.5	0.74	4.1 to 8.1			
Magnasci SRL (uRADMonitor SMOGGIE-PM v1.101)	Stationary	PM1.0	0.85	4.8 to 5.6	Optical Particle Counter	1 minute	Indoor and Outdoor
		PM2.5	0.71	2.1 to 2.8			
Met One (ES-405)	Stationary	PM1.0	0.88	2.8 to 3.6	Optical Particle Counter	1 minute	Indoor and Outdoor
		PM2.5	0.86	3.5 to 4.0			
		PM10	0.85	4.5 to 8.9			
Oizom (Polludrone Smart)	Stationary	PM1.0	0.84	4.5 to 5.0	Optical Particle Counter	1 minute	Outdoor
		PM2.5	0.79	5.4 to 6.1			
Piera Systems (Canaree R1)	Stationary	PM1.0	0.87	3.2 to 4.5	Optical Particle Counter	1 minute	Indoor and Outdoor
		PM2.5	0.8	6.3 to 7.2			
PM Monitor (iMonPM)	Stationary	PM1.0	0.83	2.2 to 3.8	Optical Particle Counter	1 minute	Outdoor
		PM2.5	0.83	3.4 to 4.3			
PurpleAir (PA-I)	Stationary	PM1.0	0.94	N/A	Optical Particle Counter	0.33 minutes	Outdoor
		PM2.5	0.91				
		PM1.0	0.95				
PurpleAir (PA-II)	Stationary	PM1.0	0.97	N/A	Optical Particle Counter	0.58 minutes	Indoor and Outdoor
		PM2.5	0.95				
		PM1.0	0.99				
		PM2.5	0.83				

Table 1 (Continued). Documented Particulate Matter Sensors

Sensor Model	Category	Pollutant Type	Field R^2	Field MAE*	Sensing Mechanism	Time Resolution	Indoor or Outdoor
PurpleAir (PA-II-FLEX)	Stationary	PM1.0	0.93	N/A	Optical Particle Counter	1 minute	Indoor and Outdoor
		PM2.5	0.83				
QuantAQ (MODULAIR-PM)	Stationary	PM1.0	0.91	4.1 to 6.8	OPC, Nephelometer	1 minute	Indoor and Outdoor
		PM2.5	0.86	4.0 to 5.2			
Redspira	Stationary	PM2.5	0.80	4.7 to 7.1	Optical Particle Counter	1 minute	Outdoor
RTI (MicroPEM)	Portable	PM2.5	0.78	6.4 to 8.3	Optical Particle Counter	0.17 minutes	Indoor and Outdoor
SailBri Cooper (SCI-901)	Stationary	PM2.5	0.84	2.2 to 3.1	Optical Particle Counter	1 minute	Outdoor
		PM10	0.73	5.6 to 14.1			
SainSmart (Pure Morning P3)	Stationary	PM2.5	0.73	4.8 to 5.4	Optical Particle Counter	0.50 minutes	Indoor and Outdoor
Sensirion (Nubo Air)	Stationary	PM1.0	0.83	2.9 to 3.5	Optical Particle Counter	5 minutes	Outdoor
		PM2.5	0.78	5.2 to 6.5			
Shinyei (PM Evaluation Kit)	Stationary	PM2.5	0.85	N/A	Optical Particle Counter	1 minute	Outdoor
Tera Sensor (NextPM)	Stationary	PM1.0	0.92	2.1 to 4.6	Optical Particle Counter	0.17 minutes	Indoor and Outdoor
		PM2.5	0.91	3.9 to 5.6			
TSI (AirAssure)	Stationary	PM2.5	0.82	N/A	Optical Particle Counter	5 minutes	Indoor and Outdoor
TSI (BlueSky)	Stationary	PM2.5	0.71	4.9 to 5.9	Optical Particle Counter	1 minute	Indoor and Outdoor

*Field mean absolute error for gaseous sensors is measured in micrograms per meter cubed ($\mu g/m^3$).

Table 2. Documented Gaseous Sensors

Sensor Model	Category	Pollutant Type	Field R^2	Field MAE*	Sensing Mechanism	Time Resolution	Indoor or Outdoor
2B Technologies (POM)	Stationary	O_3	1.00	N/A	UV Absorption	0.17 minutes	Indoor and Outdoor
Aeroqual (AQY-R)	Stationary	NO_2	0.84	2.8 to 3.1	Electrochemical	1 minute	Outdoor
		O_3	0.96	3.0 to 4.8	Metal Oxide		
Aeroqual (v1.0)	Stationary	NO_2	0.70	4.1 to 5.3	Electrochemical	1 minute	Outdoor
		O_3	0.97	2.4 to 7.3	Metal Oxide		
Aeroqual (S-500)	Portable	O_3	0.85	N/A	Metal Oxide	1 minute	Indoor and Outdoor
Airly	Stationary	O_3	0.92	19.3 to 22.9	Electrochemical	5 minutes	Indoor and Outdoor
Air Quality Egg (v1.0)	Portable	O_3	0.85	N/A	Metal Oxide	1 minute	Indoor and Outdoor
APIS	Stationary	CO	0.89	70.0 to 99.8	Electrochemical	1 minute	Indoor and Outdoor
		NO	0.92	1.3 to 2.6	Electrochemical		
		O_3	0.78	14.2 to 19.1	Electrochemical		
AQMesh (v5.1)	Stationary	CO	0.92	40.0 to 52.3	Electrochemical	5 minutes	Outdoor
		NO	0.72	10.9 to 12.3	Electrochemical		
		NO_x	0.79	15.0 to 18.9	Electrochemical		
CairPol (Cairsens)	Portable	CO	0.94	93.6 to 134.9	Electrochemical	1 minute	Indoor and Outdoor
Ecomesure (EcomSmart)	Stationary	CO	0.78	0.08 to 1.3	Electrochemical	1 minute	Outdoor
Igienair (Zaack AQI)	Stationary	CO	0.86	276 to 329.6	Electrochemical	0.50 minutes	Indoor
Kunak (Air A10)	Stationary	NO	0.81	1.1 to 1.7	Electrochemical	5 minutes	Outdoor
		O_3	0.87	4.8 to 5.9	Electrochemical		
Perkin Elmer (ELM)	Stationary	O_3	0.93	4.6 to 9.8	Metal Oxide	1 minute	Outdoor
Spec Sensors	Portable	CO	0.87	N/A	Electrochemical	1 minute	Indoor and Outdoor
UNITEC (SENS-IT)	Stationary	O_3	0.78	11.0 to 13.4	Metal Oxide	1 minute	Outdoor
Vaisala (AQT410 v1.15)	Stationary	CO	0.82	222 to 234	Electrochemical	1 minute	Indoor and Outdoor
		O_3	0.74	6.6 to 8.9	Electrochemical		
Vaisala (AQT530 v3.1)	Stationary	CO	0.92	72.2 to 85.9	Electrochemical	1 minute	Outdoor

*Field mean absolute error for gaseous sensors is measured in parts per billion (ppb).

Selecting Appropriate Monitoring Locations in Communities

The following subsections provide guidelines and recommendations on the selection of suitable locations to deploy AQS.

Guidelines and Recommendations for Selecting Monitoring Sites

Selecting practical locations for AQS is necessary for the following reasons (U.S. EPA, 2022b):

- Obtain representative measurements of air pollution concentrations to reliably evaluate potential health risks.
- Address the disproportionate health impacts from inequitable exposure to harmful pollutants encountered by DACs and Vulnerable Roadway Users (VRUs).
- Raise public awareness regarding the adverse impacts of poor air quality and how monitoring efforts can promote informed decision-making.
- Advocate for behavioral changes among community members and promote community engagement.
- Identify the various sources of air pollution in a region to help guide the formulation of targeted policies and regulations to mitigate air pollution.
- Validate air quality models to enhance their predictive capabilities by collecting accurate data from monitors located strategically in an area.

Practitioners are encouraged to consider certain guidelines and recommendations during the process of selecting monitoring sites. Locating AQS near polluting sources is one key factor. The highest levels of air pollution can be detected by strategically positioning monitoring sites close to major emissions sources such as highways, power plants, or industrial facilities (Baldauf et al., 2009). As a result, the data collected from these devices will be an accurate representation of the pollution levels exposed by residents in a community. Another important consideration in the selection of monitoring sites is meteorological conditions since wind patterns affect the transport of pollutants from nearby sources (Baldauf et al., 2009). This will help in understanding the distribution of pollutants over a geographic region.

The spatial coverage of AQS is also a key factor. The distribution of sensors in a community should be optimized—by considering population density, land use, and traffic patterns—to capture the variations in air pollution levels in the area (Lu et al., 2022). Deploying sensors at various locations will generate a detailed overview of air quality patterns across different communities, allowing for the identification of potential pollution hotspots.

Finally, practitioners should consider equity and environmental justice concerns when selecting monitoring locations. DACs often experience higher levels of poor air quality and disproportionate health burdens (Miranda et al., 2011). This highlights the need to prioritize and extend monitoring efforts in these communities to effectively capture exposure disparities (Lu et al., 2022). Furthermore, community engagement and involvement in the site selection process can ensure that monitoring sites are placed in areas that are of particular concern to the community (Madrigal et al., 2020).

Selecting Suitable Sensors for Monitoring

EPA published its 2022 *Enhanced Air Sensor Guidebook*—an update to its original 2014 *Air Sensor Guidebook*—intended to be used as a reference by users interested in collecting and interpreting measurement data (Clements et al., 2022). The agency has not formally approved any AQS to date, however, they recognize the increasing availability of sensors as well as best practices related to sensor use. Although there is a vast collection of sensors in the market to choose from, this guidebook includes information on how to optimally select a sensor for specific needs. This includes determining the purpose of collecting air quality data (such as for educational purposes or personal exposure), what pollutants the user would like to measure (such as particulate matter or gas pollutants), as well as other features like portability, storage capacity, or response time. The guidebook also includes relevant information regarding installation and general usage.

Conclusion

Addressing air pollution and its disparate impacts on communities can improve public health and achieve environmental justice. The existing literature focuses on the importance of monitoring air quality in communities to understand pollution patterns, prioritize interventions, promote equitable policies, and promote public involvement. While traditional regulatory monitors provide essential data, emerging sensing technology offers an opportunity to enhance spatial coverage, accessibility, and community engagement. However, AQS performance varies based on technology, calibration, and real-world conditions, necessitating further research.

Limitations exist with the use of AQS including accuracy of data collected and calibrating the devices. Enhancing calibration techniques and performing comparative studies between AQS and regulatory stations can validate the performance of AQS on the field. Additionally, it might be difficult for DACs to adopt these sensors due to cost, lack of technical expertise, and user acceptance. Therefore, developing a comprehensive approach to increase public awareness and involve community members can help overcome these challenges.

The evolution of air quality monitoring methods offers opportunities to create more accurate, inclusive, and responsive monitoring networks. By addressing the limitations of traditional regulatory monitors and harnessing the potential of AQS, communities can gain valuable insights into their air quality, advocate for policy changes, and actively participate in protecting their health and environment. The deployment of AQS in communities will present an opportunity to crowdsource air quality data by collecting information from several individual monitors. This will create denser and reliable air quality maps (Dybwad, 2023). One successful implementation example is the PurpleAir Map, which is one of the most extensive air quality networks with crowdsourced data from more than 300,000 PurpleAir monitors worldwide (Dybwad, 2023).

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