An overview of outdoor low-cost gas-phase air quality sensor deployments: current efforts, trends, and limitations

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Abstract. We reviewed 60 sensor networks and 17 related efforts (sensor review papers and data accessibility projects) to
10 better understand the landscape of stationary low-cost gas-phase sensor networks deployed in outdoor environments
worldwide. This study is not exhaustive of every gas-phase sensor network on the globe, but rather exists to categorize types
of sensor networks by their key characteristics and explore general trends. This also exposes gaps in monitoring efforts to date,
especially regarding the availability of gas-phase measurements compared to particulate matter (PM), and geographic coverage
gaps (the global south, rural areas). We categorize ground-based networks that measure gas-phase air pollutants into two main
15 subsets based on their deployment type: quasi-permanent (long-term) and campaign (short to medium-term) and explore
commonplace practices, strengths, and weaknesses of stationary monitoring networks. We conclude with a summary of cross-
network unification and quality control efforts. This work aims to help scientists looking to build a sensor network explore
best practices and common pathways, and aid end users in finding low-cost sensor datasets that meet their needs.

1 Introduction

20 **1.1 A Brief History of Low-Cost Gas Sensors: Context, Development, and Growth**

In the past few decades, the emergence, growth, and solidification of low-cost air quality sensor efforts have coincided with
myriad policy decisions and social movements. In this section, we will reference those in the United States (US) as examples
of possible drivers behind the expansion of low-cost sensor use. The Clean Air Act, which serves as the US's primary set of
air quality laws, was first enacted in 1963. It calls for the monitoring of six "criteria" pollutants, which are harmful to both
25 human health and the environment (EPA, accessed 9/18/2023). The criteria pollutants are: particulate matter (PM), ozone (O_3),
nitrogen oxides (NO, NO_2, NO_x), sulfur oxides, carbon monoxide, and lead. For each of these pollutants, the current guidelines
were established between 2010 and 2015 (California Air Resources Board, accessed 9/18/2023). Following the public
awareness and federal regulations of these pollutants, general air quality monitoring efforts in the US increased, and have
remained relevant to date. In 2022, the US Environmental Protection Agency (EPA) allocated over $54 million USD to fund
30 143 air monitoring projects in 37 states, many of which include low-cost sensor networks, including $20 million USD in grants

for ambient air monitoring in underserved communities (Afshar-Mohajer, accessed 9/18/2023). The affordability and ease-of-use of low-cost sensors continues to answer the need for more air quality monitoring, especially in historically underserved areas.

35   Environmental justice (EJ) refers to the unequal exposure to pollution based on factors such as race and class (Čapek, 2014), and even the placement of monitoring stations can be inequitable (Miranda et. al., 2011). In the United States, the National Association for the Advancement of Colored People (NAACP) is largely credited with formalizing the movement with their protests in the 1980's (Department of Energy, 2024). While a variety of other special interest groups, non-profit, and community organizations have been actively involved in democratizing air pollution monitoring (National Association of

40   Clean Air Agencies, accessed 9/18/2023; Coalition for Clean Air, accessed 9/18/2023), formal government recognition and action on these issues may have encouraged further monitoring efforts, including low-cost sensors. Notably, in 1992 the Environmental Equity Working Group was established by then-President George H. W. Bush, followed by Executive Order 12898 issued by then-President Bill Clinton in 1994, titled "Federal Actions to Address Environmental Justice in Minority Populations and Low-Income Populations" (Department of Energy, accessed 9/18/2023). Environmental justice and air quality

45   monitoring in underserved regions have remained focus areas of air sensor use to date (Oyola et. al., 2022).

The rise of sensor-based exposure monitoring follows a similar timeline. In their 1960 paper, Sherwood and Greenhalgh introduced a "personal air sampler" that used a filter to collect PM (1960). While a few other studies throughout the 1960's and 1970's began to broach the idea of personal air quality monitoring (Taylor, 1987; Ott, 1982; Morgan and Morris, 1976;

50   National Research Council (US) Committee on Indoor Pollutants, 1981), modern day air quality sensor technology began to emerge in the 1980's, with several studies noting the use of electrochemical (Khan et. al., 1983; Ramakrishna et. al., 1989; Weppner, 1987) and non-dispersive infrared (NDIR) gas sensors (Shibata et. al., 1987), which were new at the time. During the 1990's, other commonly used sensor technologies such as thin films (Korotchenkov et. al., 1999; Meixner et. al., 1995) and metal oxides (Papadopoulos et. al., 1996; Sberveglieri et. al., 1997; Meixner et. al., 1996) began to emerge. The early

55   2000's brought the first few noteworthy sensor network studies (Arnold et. al., 2002; Zampolli et. al., 2004; Mahfuz and Ahmed, 2005).

The mid aughts and early 2010's brought further advancements in sensor technology (Chang et. al., 2006), major improvements to sensor calibration methods (Piedrahita et. al., 2014; Spinelle et. al., 2013), and a huge influx of sensor applications, including

60   the advent of large-scale sensor networks (Postolache et. al., 2009; Ma et. al., 2008) and science-grade research projects (Mead et. al., 2013; Bales et. al., 2012; Sivaraman et. al., 2013). Government programs began endorsing and funding low-cost sensors as a supplement to traditional air quality monitoring, contributing to the burst of sensor deployments during this period. For instance, the US EPA published the first version of its "Air Sensor Guidebook" in 2014, targeted as a resource for individuals interested in low-cost sensors and sensor data (2014).

During the most recent era of low-cost air quality sensing, from the mid 2010's to present, on which this review focuses, sensor projects have continued to expand with no signs of slowing down. Each the 60 sensor networks reviewed in sections 2 and 3 originated or found widespread usage during this period, which includes the growth of low-cost sensors in university and other research groups, and the advent of large-scale sensor network companies such as PurpleAir. This era represents an exciting time when sensor networks are continuing to grow as a solution to gaps in monitoring, and gain legitimacy as monitoring tools. Figure 1 shows the number of Google Scholar search results by the decadal ranges referenced in this section for "low-cost air quality sensors outdoor stationary". While this search term is imperfect and related but irrelevant papers may still appear, it serves as a rough proxy for the explosion of low-cost sensor studies in the 2000's that is continuing into the present day.
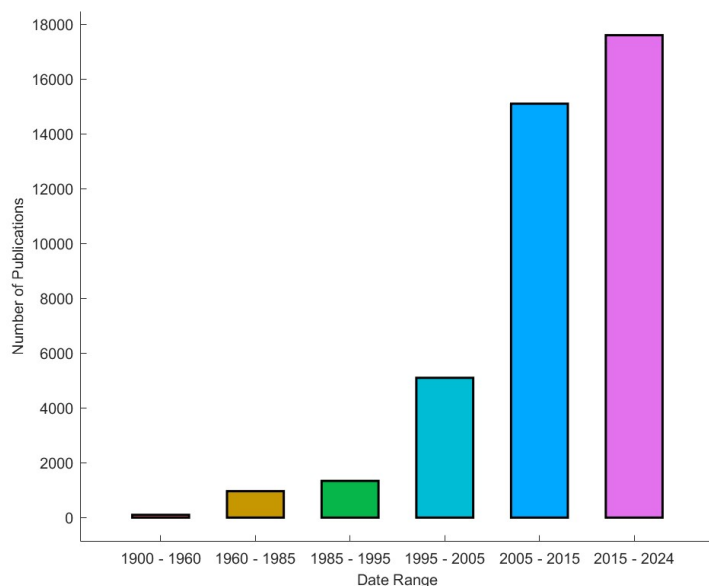
Figure 1: Number of Google Scholar search results for "low-cost air quality sensors outdoor stationary", sorted by publication date range.

1.2 The Need for Gas-Phase Sensor Networks

One of the main reasons sensor networks experienced this major growth in popularity in the twenty-first century is their ability to fill gaps in existing air quality monitoring efforts. Since low-cost sensors are a fraction of the cost of traditional air quality monitoring instruments, a fleet of them can be deployed at the same price point as one regulatory-grade monitor. Thus, low-cost sensors have been a boon in areas that have been overlooked by traditional monitoring efforts, and alike in areas with high spatial variability of pollution where a single air quality monitor is not indicative of trends across the region.

While the findings of this study and others (Carotenuto et. al., 2023) show that PM-based sensor networks are among the largest and most frequently deployed, there is a great need for more gas-based measurements. PM has traditionally been

targeted in monitoring efforts because of the adverse health effects associated with it (Donaldson et. al., 2005; Wyzga and Rohr, 2015; Pope and Dockery, 2006; Chen and Lippmann, 2009). PM measurements are particularly relevant to dust storms (Khader et. al., 2019) and widespread cookstove usage (Alexander et. al., 2018) in certain parts of the world, and in studying wildfires worldwide. However, even in regions where PM is the primary air quality concern, gas-phase chemistry has been

90   shown to drive PM emissions (Ren et. al., 2017; Quevedo et. al., 2024), necessitating data from both to understand the bigger picture.

Several volatile organic compounds (VOCs) have been shown to have severe health effects of their own, including: leukemia (Liu et. al., 2022), lung cancer (Kampa et. al., 2008), heart disease (Kampa et. al., 2008), asthma (Alford and Kumar, 2021;

95   Liu et. al., 2022; Ware et. al., 1993), and a variety of other acute and chronic health conditions (Fiedlier et. al., 2005; Cheng et. al., 2019; Johnston et. al., 2021). For these pollutants, both the concentration and length of exposure are crucial for understanding potential risks (Hu et. al., 2023), making it doubly important to have highly localized datasets to both assess personal exposure and set regulations relevant to health risks. Trace gases have been shown to vary widely in concentrations on opposite sides of the same building (Collier-Oxandale et. al., 2018), demonstrating that personal exposure can vary widely

100   even within a small radius. Again, the gas-phase data that sensors can supply on highly localized spatial and temporal scales is crucial to understanding and preventing health risks from air quality. VOCs can also contribute to ground-level ozone production, which is associated with a variety of health risks, including a variety of respiratory issues (Soares and Silva, 2022). Additionally, PM-centric sensor networks miss out on measuring greenhouse gas emissions, including methane (CH_4) and carbon dioxide (CO_2), which the present review found to be among the most studied with gas-phase sensor networks. Since

105   sensors are a valuable tool in filling monitoring gaps, this data can be influential for designing mitigation strategies or setting emission targets in areas lacking more widespread air pollution monitoring.

1.3 Nomenclature

In this work, a "sensor" refers to an individual component that typically measures one specific pollutant of interest. A "sensor package" refers to the complete measurement instrument, including one or more sensors, a circuit board, some form of data

110   collection, and a means of pulling the ambient sample across the sensors (e.g., a fan or pump). A "sensor network" refers to a cluster of several sensor packages deployed in some predetermined location. A "node" refers to an individual sensor package that is part of a sensor network.

1.4 Criteria for Inclusion in the Review

For a low-cost sensor network or associated study to be included in our review, it had to meet the following criteria:

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- The cost of an individual sensor package could not exceed $10,00 USD or equivalent
- The sensor package must measure at least one gas-phase compound
- The sensor network must be ground-based

- The sensor network must be deployed outdoors
- The sensors must be deployed in a stationary location; mobile and wearable devices were excluded

120 We focused on application-based sensor deployments rather than reports on sensor development and calibration alone. However, in regions with few gas-phase monitoring efforts, we included deployments focusing on calibration or data quality, so long as the sensors were still deployed in a stationary outdoor location.

1.5 Literature Review Methods

We began our literature review with broad Google scholar searches and relevant conference proceedings, including: NASA
125 Health & Air Quality Applied Science Team (HAQAST) 2017 - 2023 Proceedings (NASA HAQAST, accessed 9/18/2023), European Geophysical Union (EGU) Annual Meeting 2023 Monitoring Networks Session (European Geophysical Union, accessed 9/18/2023), Air Sensors International Conference (ASIC) 2022 Proceedings (Hemingway, 2022), American Geophysical Union (AGU), Thriving Earth Exchange Projects Portal (Thriving Earth Exchange, accessed 9/18/2023), and AGU Ground-Based Atmospheric Monitoring Networks Session 2022 (AGU, accessed 9/18/2023).

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Most resulting networks originated or were deployed in English-speaking or western European countries, towards which we acknowledge that our search was heavily biased, as these tend to be the areas with the most low-cost monitor coverage. For regions that were underrepresented in our initial search, we used targeted Google scholar searches to find field deployments in these areas, aiming to include multiple networks from each region. While these methods are not exhaustive, we are confident
135 that the trends in low-cost sensor practices have been illuminated with 60 sensor networks reviewed. This review was concluded in September 2023, with a few additional references added during the review process in 2024.

Several air quality sensor review papers were consulted in the writing of this manuscript, which targeted key aspects of the use of low-cost sensors and directed us toward relevant papers. These included: the use of low-cost sensors for measuring
140 VOCs (Spinelle et. al., 2017) and particulate matter (Engel-Cox et. al., 2013), deployments in Sub-Saharan Africa (Amegah, 2018), sensor types and their calibration (Narayana et. al., 2022), two summaries of performance targets for low-cost sensors (Williams et. al., 2019; Karagulian et. al., 2019), a review of campaign-style temporary sensor networks (Carotenuto et. al., 2023), and broad reviews of the use of low-cost sensors in the 2010's (Morawska et. al., 2018). Additionally, government-sponsored initiatives to compare low-cost sensors were utilized, including the World Meteorological Organization's 2021
145 report (World Health Organization, 2021), and sensor comparison initiatives published by: the European Network on New Sensing Technologies for Air-Pollution Control and Environmental Sustainability (EuNetAir) (Borrego et. al., 2016), South Coast Air Quality Management District (AQMD)'s Air Quality Sensor Performance Evaluation Center (AQ-Spec) program (Collier-Oxandale et. al., 2020), and the Community Air Sensor Network (CAIRSENSE) project (Jiao et. al., 2016).

1.6 Format

150 The format of each subsequent section and subsection is as follows. First, we define the section or subsection, explaining the characteristics of low-cost monitoring networks included within it. Following this, we dive into multiple examples of each, highlighting the characteristics mentioned in the introductory paragraph and providing more specific details and context. We conclude by summarizing the common threads in each category, exploring emerging sensor directions, and making recommendations for sensor usage and data management based on our findings.

2 Quasi-Permanent Low-Cost Sensor Networks

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Quasi-permanent networks are deployed in stationary locations with the intent of measuring for at least two years or the remainder of the sensor's useful life. These often feature country-wide or global calibration schemes, and are the most likely to include a live dashboard for end users to visualize the data. Most sensor packages that we reviewed which fell into this category were operated by local or regional governments, or consist of widely-deployed sensor packages developed by private

160 companies. Many of these do not list specific calibration procedures, some from a lack of standardized calibration, but others for proprietary reasons as data is part of their product. A list of the 12 quasi-permanent networks considered in this review and their key characteristics can be found in Table 1.

2.1 Quasi-permanent, operated by private companies

Most sensor networks in this category are operated by for-profit companies. The typical framework is as follows: the company

165 will manufacture and sell the sensor packages widely for profit. Each of the individually owned sensor packages becomes part of a publicly-available data map, which anyone can visit to visualize the air quality in their area. These maps sometimes include data from regulatory monitors or other sensor networks, and typically focus on air quality index (AQI) as a key metric. While live or semi-live data is often accessible, historical data may not be available for download, or may require the use of an application programming interface (API), which may present a barrier to non-scientific users from downloading it for further

170 inspection. Seven such companies are reviewed in this section, with the largest, PurpleAir, discussed in sect. 2.1.1.

A case study of a company born out of a university research grade project is TELLUS and its AirU sensors. The project was originally started at the University of Utah under a National Science Foundation (NSF) grant to bring higher spatial coverage air quality monitoring to the Wasatch Front region of Utah (AIRU, accessed 9/18/2023). Since then, it has evolved into a

175 product line of indoor and outdoor sensor packages measuring CO, NO_2, and PM. As is typical of university research projects, the sensors are robustly calibrated via chamber tests (Sayahi et. al., 2019; Kelly et. al., 2017), colocation with reference grade instruments (Becnel et. al., 2019a; Sayahi et. al., 2020; Kelly et. al., 2017), and the development of machine-learning based calibration algorithms (Becnel et. al., 2019b; Becnel and Gaillardon, 2021). TELLUS' website includes its own live data map dubbed AirView which includes data not only from the Tellus sensor packages, but also incorporates data from two larger

180   quasi-permanent monitoring networks: PurpleAir, discussed in sect. 2.1.1, and the US EPA's AirNow, discussed in sect. 2.2 (AirView Map by TELLUS, accessed 9/18/2023). This dashboard represents a recurring approach of incorporating data from other networks to fill in gaps in spatial distribution, but does not feature a historical data archive for download. The sensors have been utilized in at least one ender's peer-reviewed study (Mullen et. al., 2023).

185   IQAir, a company based in Switzerland, produces a line of low-cost sensor packages measuring CO_2 and PM (IQAir, accessed 9/18/2023). Its live data map has high spatial coverage in North America, Europe, East and South Asia, and Oceania. Their map also includes data from third-party sensors such as PurpleAir and Clarity (IQAir Live Animated Air Quality Map, accessed 9/18/2023). Historical data and other tools can be accessed via API. Its AirVisual app uses real-time weather and global satellite data in addition to its low-cost sensor data on the map to better predict air hourly air quality. Their website describes using
190   machine learning to validate and calibrate data based on the environmental conditions, and estimating the AQI where monitoring gaps exist (IQAir AirVisual Platform, accessed 9/18/2023).

Clarity is a privately-owned company that likewise sells sensor packages meant for long-term deployments, targeting NO_2, O_3, and PM (Clarity Movement Co., accessed 9/18/2023). It also features a live data dashboard called openmap, which includes
195   data from both the Clarity sensor nodes and government reference stations alike. Clarity also produces a data tool which allows the user to view and plot historical data from individual nodes (Open Map - Clarity Movement, accessed 9/18/2023). The map has worldwide coverage, with the highest sensor density in North America and Europe. Asia and the global south receive considerably less spatial coverage. One end-user led deployment saw the sensors colocated with reference monitoring stations to develop calibration algorithms (Zaidan et. al., 2020).

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AirGradient is another privately held company with sensors measuring CO2, NOx, PM, and VOCs (AirGradient, accessed 8/26/2024). Different versions of the platform are available for indoor and outdoor monitoring. It also features a live data map, where near real time data as well as data up to two weeks old can be visualized. The map has worldwide coverage, with the highest sensor density in North America and Europe. An interesting feature is that the AirGradient platform uses open-source
205   hardware, offering both completed sensor packages and build kits for project-oriented customers. The sensors have been co-located in more than 20 different locations globally as of 2024, and calibration fits have been derived to assess goodness of fit, although the model specifications are not explicitly stated on their website. While the first few scientific studies using AirGradient sensors pertain to indoor air quality (Chatzidiakou et. al., 2023) and outdoor PM (Hodoli et. al., 2024), the network has potential for future outdoor gas-phase studies.

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2.1.1 Case Study: PurpleAir

PurpleAir is the largest low-cost air quality sensor network across the globe, with over 22,000 PM sensors deployed across approximately 100 countries as of 2023 (PurpleAir, Inc., accessed 9/18/23). It offers a live global map where users can toggle between raw sensor data and several different Air Quality Index (AQI) calculations based on the data at hand (PurpleAir Real-Time Air Quality Map, accessed 9/18/2023). While there is no easy click-and-download option, an API can be used to access historical data. As of 2024, fees may be incurred for downloading historical data depending on the amount of data requested.

For quality assurance, PurpleAir relies on the sensors' dual channel laser configuration. If the two laser channels read similarly, the data is deemed reliable. If not, the sensor will appear semi-translucent on the map with a highlighted warning if a user selects the sensor online. The confidence score between the two channels is also displayed with either a check mark or an X accordingly. Even with this feature, various agencies have reported that the raw PurpleAir data may exceed actual values by a factor of two in experiments comparing them with reference-grade PM instruments (Air Quality Sensors, accessed 9/18/2023). Likewise, the Plantower sensors used in the PurpleAir nodes have a functional life of approximately two years (PurpleAir Community, accessed 9/18/2023), but as of 2023 there is no mechanism to remove sensor data from the map based on sensor age alone.

In recent years, PurpleAir has launched an add-on VOC sensor (Bosch BME688) to its existing PM sensor packages, but they have yet to reach the same widespread use as the original PurpleAir monitors. As seen in Fig. 2, there are far fewer VOC-enabled PurpleAir sensors worldwide than their standalone PM sensors. The AQI and calibration procedures for the VOC sensor have yet to be formalized, with only the raw sensor signal available on PurpleAir's interactive map rather than a calibrated mixing ratio estimate. Even within wealthier countries, socioeconomic disparities affect the spatial distribution of PurpleAir monitors (Sun et. al., 2022).
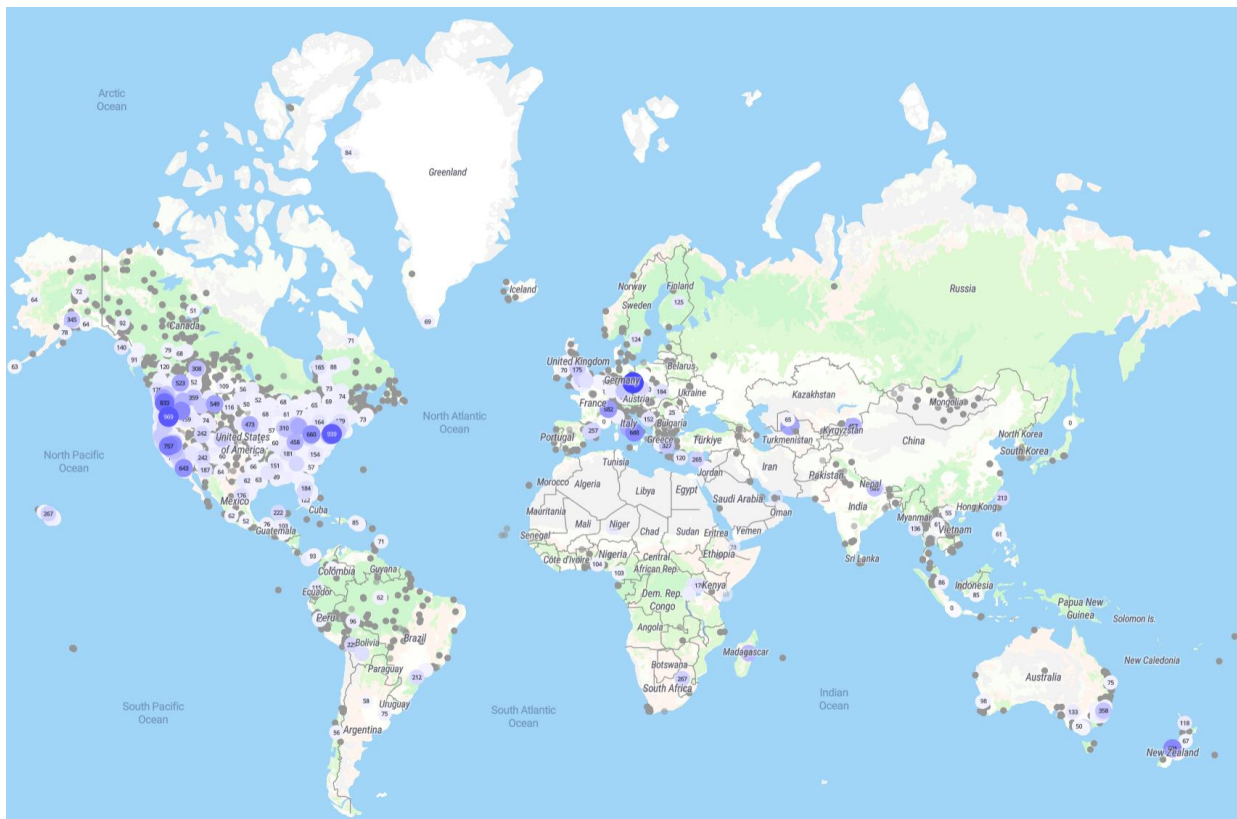
Figure 2: Usage of outdoor PurpleAir VOC sensors (colored in shades of purple based on concentration) with additional PurpleAir PM-only sensors marked in gray. The map shows that global coverage for VOCs is sparser than for PM, with the global south and rural areas lacking gas-phase coverage. PM coverage is also significantly less dense in the global south. (Copyright PurpleAir, source: map.purpleair.com, retrieved 2023/09/18).

Since PurpleAir is an affordable, user-friendly sensor with built-in mapping capabilities, many research groups utilize their products to collect air quality data. However, since the data quality is not necessarily science-grade, many research groups have conducted pilot deployments to generate more reliable calibration algorithms, rendering the PurpleAir data more useful. We encountered many cases of research groups using the PurpleAir monitors as their low-cost sensing platform, often opting to develop their own calibration algorithms to ensure accuracy. Studies concerning the PurpleAir VOC sensor and its calibration are few as of 2023; although the VOC sensor is a newer addition to the PurpleAir product line, they appear to be underutilized in addition to being under-deployed. We reviewed one study which compared the VOC sensor data to an air quality dispersion model of VOC mixtures emanating from an industrial facility in the northeastern United States (Rosmarin et. al., 2023). Another study in the Ohio River Valley in the US utilized both PurpleAir and AirViz monitors to measure PM and VOCs. While regression-based calibration algorithms were derived for PM, raw VOC outputs were used for qualitative analysis only (Raheja et. al., 2022).

250 Most other studies concerning PurpleAir have focused on PM sensing. Many have focused on improving calibration for monitoring during fire and smoke events (Barkjohn et. al., 2020; Barkjohn et. al., 2022; Sablan et. al., 2022), while others have used them in community-level monitoring and citizen science applications (Lu et. al., 2022; AirWatchSTL, accessed 9/18/2023; Jing et. al., 2022; Byrne et. al., 2023). Additional US-based studies have utilized the PurpleAir monitors and developed their own calibration algorithms for general usage (Malings et. al., 2020; Tryner et. al., 2020; Wallace et. al., 2022).

255 Internationally, PurpleAir PM data has also been utilized extensively, especially in the global south where gas-phase measurements and air quality measurements generally are sparse compared to other regions (BKH Outdoor Sensor Network, accessed 9/18/2024; Awokola et. al., 2020; Awokola et. al., 2022; Velasquez et. al., 2022; Coker et. al., 2022; Campmier et. al., 2023).

260 A host of other air quality monitoring tools incorporate data from PurpleAir into their interface, including the US EPA's AirNow's Fire & Smoke Map (AirNow Fire and Smoke Map accessed 9/18/2023), AirView by Tellus (AirView Map by TELLUS, accessed 9/18/2023), AirVisual by IQAir (IQAir Live Animated Air Quality Map, accessed 9/18/2023), Air Matters (mobile app, accessed 9/18/2023), Windy (mobile app, accessed 9/18/2023), Paku for PurpleAir (mobile app, accessed 9/18/2023), Local Haze (mobile app, accessed 9/18/2023), and AirCare (mobile app, accessed 9/18/2023).

265 **2.2 Quasi-permanent, operated by government**

A small number of quasi-permanent low-cost sensor networks operated by various government entities were reviewed to understand how sensors are being used to complement traditional regulatory tools. These government-operated networks typically make use of commercially available sensors (although not always), include a live data dashboard for easy data visualization, and incorporate regulatory monitoring station data for comparison on the data dashboard or elsewhere on their 270 site.

The most widely recognized usage of low-cost air quality sensors by the US government is the Environmental Protection Agency's (EPA) AirNow program. While the main AirNow interactive map only displays regulatory-grade ozone and PM data from government agencies (AirNow, accessed 9/18/2023), the AirNow Fire & Smoke map also includes data from 275 PurpleAir's low-cost PM sensors. The inclusion of these sensors greatly improves spatial coverage, but reduces confidence in the data as the PurpleAir sensors are not held to the same rigorous standards as the government-run analyzers. However, the Fire & Smoke map is targeted towards the public for real-time decision-making during wildfire and other emission events, with the locations of fires also shown on the map and resources about the fires and safety available (AirNow Fire and Smoke Map: Getting Started, accessed 9/18/2023). Data from the main AirNow site has been used in scientific applications (Chai et. 280 al., 2017) in addition to individual and community-level decision making.

Several municipalities and programs in the United States use Lunar Outpost's Canary sensor packages for local and regional monitoring, including the US Forest Service, US EPA, and the Denver Department of Public Health and Environment's Love my Air program (Outpost Environmental, accessed 3/8/2023). Love my Air has measured PM at schools in the Denver metropolitan area using the Canary modules since 2018, and now includes a few sites measuring a broader range of pollutants, including: O_3, CO, NO, NO_2, H_2S, SO_2, and VOCs. It includes its own data visualization map with data from both the sensors (marked with circles) and nearby regulatory monitors (notated with squares) (Love My Air, accessed 9/18/2023). The program aims to raise community awareness about local air quality issues, and includes a downloadable education outreach curriculum for teachers to share with their students. In a similar vein, the Love my Air Wisconsin program began in the fall of 2023 (Children's Health Alliance of Wisconsin, accessed 3/8/2024).

Government-run air quality monitoring utilizing low-cost sensors is most prevalent in the US and western Europe. The Dutch National Institute for Public Health and the Environment (RIVM) has incorporated low-cost sensors measuring NO_2 and PM into its monitoring and citizen science projects, with approximately 30 sensors being operated directly by RIVM as of 2019. Outdoor colocation with a reference measurement and multivariate linear regression are used to calibrate the NO_2 sensors, and the humidity dependence of the PM sensors has also been studied (Wesseling et. al., 2019). RIVM has also created an interactive map ("Measuring Together") to merge data from a variety of sensors - both their own and those deployed by various citizen scientists - with other public information including regulatory-grade air quality measurements, real-time traffic, and satellite data (RIVM Data Portal, accessed 9/18/2023). For individuals to add their data to the site, they must include information on the type of sensor and how it was calibrated to ensure data quality. As of 2019, RIVM has been working on an API to allow end users to download data from the site in bulk (Wesseling et. al.).

2.3 Quasi-permanent, operated by research institution or university

Few long-term monitoring networks are operated by research institutions or universities; most networks in this category are utilized for short-term deployments (see sect. 3.1) or as commercial products (e.g Tellus, described in sect. 2.1). However, one notable sensor network in this category is the Berkeley Environmental Air-quality & CO_2 Network (BEACO$_2$N) (BEACO$_2$N, accessed 4/8/2023). The BEACO$_2$N nodes are widely deployed in the San Francisco Bay Area, with a few nodes in other select cities worldwide. BEACO$_2$N focuses on CO_2 measurements, but also includes sensors for a variety of other pollutants (O_3, NO_2, CO, PM), making them broadly applicable in various monitoring efforts. Their website features both a live map of sensor readings and an easy-to-use data selection tool, which allows users to download historical data for selected date and location ranges. Their data also features robust calibrations based on comparison with reference-grade instruments (Shusterman et. al., 2016) and field calibration and evaluation (Kim et. al., 2018). While the global coverage of this network is not as dense as many of the commercialized networks discussed in sect. 2.1, BEACO$_2$N's data quality is high due to their data management practices, as compared to others which leave quality assurance up to the end users.

315 Another project with long-term goals is SmartCitizen, developed by Fab Lab Barcelona in Spain. Offerings include two different varieties of sensor packages: a build-it-yourself kit, targeted at citizen scientists and educators, and a more robust sensor platform designed for long-term outdoor use, with more flexibility of sensors to be included and higher accuracy. (Smart Citizen Kit, accessed 9/18/2023). The latter can accommodate sensors for CO, CO_2, NO_2, O_3, VOCs, and PM (Camprodon et. al., 2019). It also features a global map with sensors deployed on each continent, which is still live as of 2024, although few

320 nodes still appear to be logging live data (Map of SmartCitizen Kits, accessed 9/18/2023). While the environmental dependencies of the sensors and field validation efforts are offered, there is no explicit scheme to correct the sensor readings, instead utilizing the raw signals from each (Camprodon et. al., 2019).

2.4 Quasi-permanent, operated by non-profit

Here we discuss two different models of non-profit sensor networks in the quasi-permanent category: sub-networks that

325 employ monitors purchased from the large, privatized sensor manufacturers, and non-profit sensor networks that build out their own sensor packages. Most serve a single community or region facing air quality issues. These networks tend to exist on smaller scales than their for-profit counterparts, with a smaller number of nodes per network and smaller spatial reach. While each of the networks we encountered in this category featured a live data map, we did not encounter any with a historical data archive or download option, nor any obvious explanation of data quality or calibration procedures on their websites. However,

330 even if the data is not science-grade, these networks can be crucial to building community interest and understanding of local air quality issues.

One example of a non-profit utilizing commercially purchased sensors is MKE Fresh Air Collective (MKE Fresh Air Collective, accessed 9/18/2023), a community-led non-profit organization based in Milwaukee, Wisconsin, USA. It aims to

335 provide neighborhood-scale monitoring and address environmental racism through community action. It utilizes sensors purchased via IQAir, and the data can be viewed by zooming to Milwaukee on the main IQAir map. This is an attractive model for community groups and other organizations or individuals with low technical skills and/or limited time to utilize pre-existing resources rather than having to develop their own. However, this also often means that the non-profit is limited to the calibration and visualization tools of the host network, which may be inadequate for some user needs.

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A small number of non-profit organizations develop their own sensor packages and make them available for sale, typically on a much smaller scale than the for-profit networks. One example is Ribbit Network (Ribbit Network, accessed 9/18/2023), a non-profit organization that targets teachers and citizen scientists to deploy their CO_2 sensors. Their offerings include a pre-fabricated sensor package, or the materials for the end user to build it themselves, which is targeted towards K-12 education

345 outreach efforts. Ribbit likewise has developed its own global map to view CO_2 levels from its sensors worldwide, and offers publicly available short-term data downloads. While calibrations are underway, there are no peer-reviewed studies using this network as of early 2024.

Table 1: Quasi-Permanent Sensor Networks Reviewed and Selected Characteristics

Sensor Network	Organization Type	Affiliation	Location	Pollutants	Calibration Method(s)
AirGradient	Company	AirGradient Co.	global	CO_2, NO_x, PM, VOC	Colocation with a reference instrument
AirNow	Government	US Environmental Protection Agency	USA	O_3, PM	Defer to sensor manufacturer
AirU	Company (born out of university)	TELLUS (born out of Univ. Utah NSF grant)	USA	CO, NO_2, PM	Colocation with a reference instrument
AirVisual Outdoor	Company	IQAir	global	CO_2, PM	Not reported
BEACO2N	Research Institution or University	The University of California, Berkeley	Oceania, UK, USA	CO, CO_2, NO_2, O_3, PM	Colocation with a reference instrument
Clarity	Company	Clarity Movement Co.	global	NO_2, O_3, PM	Colocation with a reference instrument
Love my Air Denver	Government	Denver Dept. of Public Health & Environment	USA	CO, H_2S, NO, NO_2, O_3, PM, SO_2	Colocation with a reference instrument
MKE Fresh Air Collective	Non-profit	MKE Fresh Air Collective	USA	O_3, PM, VOC	Defer to sensor manufacturer
PurpleAir	Company	PurpleAir, Inc.	global	PM, VOC	Varies by end user
Ribbit	Non-profit	Ribbit Network 501(c) non-profit	Europe, UK, USA	CO_2	Colocation with a reference instrument
RIVM Measuring Together	Government	Dutch National Institute for Public Health & the Environment	Netherlands	NH_3, NO_2, PM	Colocation with a reference instrument
SMARTCITIZEN	Company (born out of university)	Smart Citizen (born out of Institute for Advanced Architecture of Catalonia)	global	CO_2, PM, VOC	Colocation with a reference instrument

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3 Campaign-Based Low-Cost Sensor Networks

The remainder of the sensor networks reviewed are campaign-based, deploying sensors for a limited timeframe to study a point source or phenomenon local to the geographic area. The data quality in this category varies widely, with government and university groups typically producing the highest quality data, while non-profit or smaller commercial networks may include

355   less quality assurance. A few examples from each subcategory are described in detail here, with at least one example from a country outside the US or western Europe for each. Nearly 50 campaign-based networks are summarized here, with myriad others that sit slightly outside the scope of our review cited for further reading, but not discussed in detail. All of the former can be found in Table 2.

360   **3.1 Campaign, operated by research institution or university**

We encountered more research-grade campaign-based studies using low-cost air quality sensors than all other categories combined. In this section, we select a few key projects from each global region to review in detail. The US, western Europe, and parts of southeast Asia are more thoroughly covered in these studies than any other region, and a portion of studies concerning the global south were conducted by American or western European institutions, albeit usually with local

365   collaborators. Research-grade projects tend to have the highest data quality and most robust calibration procedures, including an ambient colocation with a reference grade instrument and an algorithm to relate the signals of each. These also tend to include the highest number of pollutants being measured by each sensor package. However, these often lack a central data portal for stakeholders to visualize or access data easily. Note that at least one example deployment is included for each campaign, but is not intended to be an exhaustive list of every use case of each sensor network. Regional boundaries have been

370   defined for illustrative purposes only; regions do not necessarily represent similarly-sized populations, nor an equal number of countries. While most of the sensor packages utilized in this category are in-house built by the research institution, we encountered a small number of research institutions that made use of sensor packages built by commercial manufacturers. In these cases, we list the name of the manufacturer, and also cite the research group responsible for deploying them.

3.1.1 Campaign, operated by research institution or university in North America

375   Campaign-based low-cost gas-phase sensor networks are abundant in North America, especially the United States. In Canada, we found that PM studies were more common, including the measurement of wildfire smoke (Si et. al., 2020; Lee et. al., 2024; Jaafar et. al., 2024). A research team at Carnegie Mellon University developed the Real-time Affordable Multi-Pollutant (RAMP) air quality sensor packages, measuring CO, NO_2, O_3, SO_2, and PM. A dense sensor network was established near Pittsburgh, Pennsylvania, USA, to better understand urban emissions (Tanzer et. al., 2019; Li et. al., 2019; Tanzer-Gruener et.

380   al., 2020), and a shorter-term campaign was conducted in San Juan, Puerto Rico following Hurricane Maria in 2017

(Subramanian et. al., 2018). Another set of sensors was deployed in British Columbia, Canada, to characterize emissions inside of a parking garage (Liu et. al., 2021). These sensors have also been deployed in various African countries (Bahino et. al., 2021). Calibration efforts include colocation with a reference instrument and subsequent modeling including: linear and quadratic regression, clustering, neural networks, Gaussian processes, and hybrid random forest models (Malings et. al., 2019; Zimmerman et. al., 2018; Jain et. al., 2021). Their data is hosted on Google Drive for greater public access.

Another noteworthy US-based project is the University of Colorado Boulder's "pods". The in-house built nodes contain sensors for: CO, CO_2, NO_2, O_3, VOCs, and PM (Piedrahita et. al., 2014). Several studies detail the calibration and validation of their sensors, which typically utilize an outdoor colocation with a reference grade instrument and the use of machine learning techniques such as artificial neural networks (Casey et. al., 2019) and multivariate linear regression (Collier-Oxandale et. al., 2018). Additional techniques have rendered its VOC sensors applicable for speciated hydrocarbons such as methane and formaldehyde (Okorn and Hannigan, 2021) in oil and gas monitoring applications (Cheadle et. al., 2017; Collier-Oxandale et. al., 2020; Okorn et. al., 2021). An offshoot of the network, Inexpensive Network Sensor Technology for Exploring Pollution (INSTEP), uses the same sensors in applications primarily concerning comparison with remote sensing instruments (NASA Ames INSTEP, accessed 3/8/2024). Neither iteration of the project features a public-facing data dashboard or download option.

While the ARISense low-cost monitors for CO, NO, NO_2, O_3, and PM are primarily US-based, they have also been deployed in Malawi in East Africa. The sensor packages were built in-house by Cross et. al. (2017), and have since been used by researchers with a variety of affiliations, including North Carolina State University. After colocation with a reference-grade instrument, a series of different machine learning models were tested to best fit the data: hybrid k-nearest neighbors, random forest hybrid, high-dimensional model representation, quadratic regression, and multivariate linear regression (Bittner et. al., 2022). Deployments in both Massachusetts, USA and Malawi were effective (Cross et. al. 2017), although the authors note the lack of reference monitoring stations in Malawi hindered their ability to regularly re-calibrate the sensor nodes.

3.1.2 Campaign, operated by research institution or university in Europe

Spatial coverage of low-cost sensors in Europe is among the highest of all the regions, but this is dominated by sensor usage in western European cities; rural areas and eastern Europe lack coverage. A recent ozone sensor calibration study in Poland (Badura et. al., 2022) suggests that outdoor sensor usage is beginning to gain traction, but we only encountered a few application-based studies in eastern Europe.

One eastern European example is the Czech Technical University in Prague's Trafficsensnet project. It involved deploying approximately 20 in-house built sensor packages measuring CO, NO_2, SO_2, VOCs, and PM in Prague to better understand the air quality effects of traffic in the urban area. Colocation with reference grade instruments was used to validate the sensor readings, although no additional calibration algorithms were fit (Brynda et. al., 2015). The project was later expanded to

include an online data portal and map-style viewer (Brynda et. al, 2016), which is unusual for university research grade

415   projects. In later iterations of the project, however, the gas-phase sensors were removed to focus on PM (Brynda et. al., 2020).

We also include studies conducted in Siberia or Russia with the eastern European countries as they exhibit a similar lack of coverage, albeit for a much larger geographic area. We encountered one PM study in the region (Lin et. al., 2020) and one study using spatially-distributed passive sampling (Khuriganova et. al., 2019), but no true gas-phase low-cost sensor studies,

420   highlighting the need for more monitoring and availability of data in this region. A related 2023 paper (Labzovskii et. al., 2023) explains the challenges of maintaining air quality networks in this region despite the high demand for localized air quality data, citing issues such as data access and decentralization. As of August 2024, there were two PM nodes logging data in Russia on PurpleAir's live map (PurpleAir, accessed 8/26/2024).

425   The remaining sensor networks reviewed in this section hail from western European countries, which are generally wealthier (Brzeziński et. al., 2020) and see much higher low-cost sensor usage. A recent project that served several European countries was Barcelona Technical University's in-house built CAPTOR box measuring ozone in Spain, Italy, and Austria (Barcelo-Ordinas et. al., 2021). Outdoor colocations with a reference instrument were conducted in each country, and different linear regression models were used to calibrate each set of sensor packages. This CAPTOR deployment was one of the few that

430   serviced urban, suburban, and rural sites in one deployment to examine differences among them (Barcelo-Ordinas et. al., 2019).

The CarboSense project out of ETH Zurich, Switzerland, deployed over 300 sensor nodes measuring CO_2 throughout Switzerland, with many of them concentrated in the city of Zurich. The sensors were manufactured by Decentlab GmbH and calibrated in-lab as well as via ambient colocation with a regulatory grade instrument. The subsequent calibration algorithms

435   were based on the Beer-Lambert law and included corrections for abnormal humidity readings and drift correction over time. The sensors showed high accuracy during the approximately two-year long deployment, but were insufficient in capturing small regional gradients (Müller et. al., 2020).

The AIRQino platform was developed by the Italian National Research Council as a sensor package to measure CO, CO_2,

440   NO_2, O_3, and PM. While it has primarily been used in mobile (Zaldei et. al., 2015) and PM-focused studies (Brilli et. al., 2020; Brilli et. al., 2021), one recent application tested its effectiveness for measuring CO_2 in the arctic in several locations on Svalbard, Norway, an island in the arctic circle. The sensors were colocated outdoors with a reference instrument and although no further calibration algorithms were derived, the AIRQino sensors showed strong agreement with the reference signals, even in the extreme cold (Carotenuto et. al., 2020).

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Several low-cost monitoring projects have sprung up in France in recent years, including the Cairbox monitoring platform, which has been used to monitor reduced sulfur compounds H_2S and CH_3SH at and around a wastewater treatment plant. This

study was a collaboration between researchers from IMT Mines Alès, a university in France, and the sensor manufactuer, Cairpol. The sensors showed strong agreement with theoretical concentrations, but no calibration factors were applied (Pereira-Rodrigues et. al., 2010). Despite the lack of further studies with this sensor platform, we have opted to include it here as it is one of the few sulfur compound monitoring efforts we encountered.

The UK is a hotbed for low-cost sensor studies, including some high-profile deployments. A network of sensor packages known as SNAQ boxes (Sensor boxes for Air Quality measurements) designed and built by the University of Cambridge measure CO, CO_2, NO, NO_2, O_3, SO_2, VOCs, and PM. In-laboratory calibrations were conducted, and were further validated via colocation with an outdoor regulatory grade instrument (Popoola et. al, 2018). The SNAQ boxes have been utilized in applications ranging from a high-density network in and around the London Heathrow Airport (Popoola et. al, 2018) and international deployments in Nigeria (Omokungbe et. al., 2023), China (Ouyang et. al., 2016; Shi et. al., 2019), and Portugal (Borrego et. al., 2016).

Elsewhere in the UK, researchers at the University of Sheffield have made use of Envirowatch Ltd.'s "E-MOTE" sensor packages to measure CO, NO, and NO_2 throughout the city. Note that although the complete sensor packages were purchased from a manufacturer, this study is included under university efforts because the manufacturer does not appear to provide recommendations or resources for calibration, data storage, or analysis as of 2024 (E-MOTE – Envirowatch Ltd., accessed 4/8/2024). For this study, the sensor packages were calibrated by the university team via colocation with a regulatory grade instrument and subsequent supervised machine learning approaches, including linear regression and generalized additive models. Overall, the sensor network was able to demonstrate the diurnal, weekly, and annual variation of pollutants in Sheffield (Munir et. al., 2019).

3.1.3 Campaign, operated by research institution or university in the Middle East

While very few sensor network studies within our criteria for inclusion have been conducted in the Middle East to date, a few related studies suggest that sensor use in the region may be gaining momentum. We came across several of PM-focused studies in the region (Khader et. al., 2019; Saleh and Kader et. al., 2022; Karaoghlanian et. al., 2022; Yavus et. al., 2021; Ozler, 2018), and one using air quality sensors onboard an uncrewed aerial vehicle (Al-Hajjaji et. al., 2017). A recent study from the Cyprus Institute performed a yearlong outdoor colocation of low-cost CO, NO_2, O_3 and SO_2 sensors with reference-grade instruments (Papaconstantinou et. al., 2023); while this study lacked a wider field component, it marks an important step for sensor measurements in the region.

A notable study comes from the Israel Institute of Technology, where CanarIT sensor packages were deployed to measure NO_2, O_3, VOCs, and PM at sub-neighborhood scale. Linear regressions were used to improve data quality after the sensor

packages were colocated with reference grade instruments. A "rolling forwards field calibration procedure" was also introduced in which calibration coefficients for each subsequent day were based on reference data from the previous three days, but would require further testing to be considered a viable method. Overall, the deployment identified hotspots within the neighborhood (Moltchanov et. al., 2015).

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In Doha, Qatar, researchers from the Qatar Mobility Innovations Center developed a low-cost sensor platform dubbed MGMS: Multi-Gas Monitoring Stations. Each node included in the initial study measured O_3, NO_2, H_2S, and CO, while additional nodes added later measured each of these in addition to SO_2, NO, and PM. The team used the sensors to estimate the AQI around various locales of the city rather than precise concentrations, so robust calibrations were not used in this aim (Yaacoub

490   et. al., 2013).

3.1.4 Campaign, operated by research institution or university in South Asia

While there are several notable monitoring efforts in India, overall monitor density is low (Brauer et. al., 2019) and largely focuses on urban areas (Agrawal et. al., 2021). Other monitoring efforts in India focus on PM (Sahu et. al., 2020), but will not be described in detail here as they lie outside the scope of gas-phase monitoring. Recently, a US-based research group deployed

495   their MPAQS (Multi-Pollutant Air Quality Sensor) packages in Delhi, India, measuring CO, NO_2, O_3, SO_2, and PM. Although colocations with research-grade instruments took place, calibration algorithms were not developed in this application, and factor analysis was later used to relate these measurements to local sources (Hagan et. al., 2019).

At Lahore University of Management Sciences in Pakistan, the VIEW (Volunteer Internet-based Environment Watch) project

500   aimed to monitor urban emissions. The in-house built sensor packages measured CO, O_3, and SO_2 and were deployed around Lahore. Detailed information on their calibration and deployment results have yet to be formally released, but this project still marks a rare low-cost monitoring network in Pakistan. Another sensor network measuring CO and PM performed its pilot study in Vadodara, India. Preliminary results from this study further demonstrate the need for more gas-based monitoring in the country (Barot et. al., 2020).

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Elsewhere in India, the SATVAM (Streaming Analytics over Temporal Variables from Air quality Monitoring) initiative tested various calibration schemes and proposed a non-parametric algorithm as the most robust to sensors located in vastly different environments: Delhi and Mumbai. These in-house built sensor packages built by the Indian Institute of Technology measured NO_2 and O_3. The proposed calibration algorithm consisted of a distance-weighted k nearest neighbors approach with a learned

510   metric, which proved effective when deploying the monitors across cities and seasons (Sahu et. al., 2021).

3.1.5 Campaign, operated by research institution or university in East Asia

Air quality issues in East Asia are complex (Jeong et. al., 2013), and in recent years low-cost gas-phase sensors have been able to help fill gaps in monitoring throughout the region, though most studies have concerned urban areas. Most East Asian studies we encountered were based in China.

A research team from the Chinese Academy of Sciences used in-house built sensor packages to measure CO, NO_2, O_3, and SO_2 in Beijing, China. Throughout the yearlong study, the sensors were robustly calibrated using single and multiple linear regression, random forest regression, and neural networks after outdoor colocation with nearby reference grade instruments. The sensors were tested under different pollution levels and environmental conditions, although the resulting data appeared to be biased based on the calibration model (Han et. al., 2021).

Another study in Beijing, China, was carried out by Tsinghua University and collaborators at two universities based in the US. In-house built sensor packages were deployed on rooftops throughout Beijing to measure CO_2, NO, NO_2, O_3, and PM. The sensors were calibrated for ozone only via colocation with a reference instrument, and best-fit linear regressions were generated. Sizable variation was seen in outdoor ozone concentrations across the city (Liu et. al., 2020).

A research group at the City University of Hong Kong developed their own MAS (Mini Air System) to monitor ambient CO, NO_2, and PM in Beijing, China. The sensors were calibrated in both laboratory and field settings. After an outdoor colocation with reference grade instruments, linear corrections were applied to the gas-phase sensor outputs. One notable application included the use of the sensor network to measure pollution at stationary locations along the Hong Kong Marathon route (Sun et. al., 2016).

Another study sought to characterize ozone in Hong Kong's greater bay area using Portable Air Stations (PAS) sourced from Sapiens, a private company. A team from the Hong Kong University of Science and Technology deployed the PAS monitors to measure NO, NO_2, and O_3. An outdoor calibration was conducted with a government-run air quality monitoring station prior to deployment, and the sensor measurements were later used as inputs in a chemical transport model (The Nested Air Quality Prediction Modeling System, NAQPMS) to better characterize a high ozone event that occurred in 2016 (Chen et. al., 2024).

Outside of China, a Tokyo Institute of Technology study measured NO_2 concentrations in the university's surrounding area using in-house built sensor platforms. An in-lab calibration was utilized to correct the sensor response for different temperature and humidity conditions. Through the sensor's wireless network, measured NO_2 concentrations were frequently compared with other sensors and nearby regulatory grade monitors for auto-calibration purposes. Overall, the network proved effective in discerning air quality differences throughout the city, including anomalies in NO_2 (Tsujita et. al., 2005).

At the National Taiwan University, in-house built CO sensor packages were deployed throughout Taipei near major roadways to determine the air quality effects of traffic in the city. The sensors were colocated at an EPA reference station, and a segmented linear regression approach was used to calibrate the sensors, since there only appeared to be a linear relationship between sensor voltage and reference concentration above a certain threshold. The study provided street-level insights into pollution from traffic, with tangible differences between weekdays and weekends as well as between rush hour and regular traffic (Wen et. al., 2013).

Researchers at Seoul National University employed a network of self-built CO_2 monitors dubbed SNUCO2M (Seoul National University CO_2 Measurement) to better understand CO_2 fluctuations in Seoul, South Korea. The sensors were colocated with reference grade instruments to ensure reliable functioning before full deployment in Seoul. The study demonstrated the characteristics of urban CO_2 throughout the city (Park et. al., 2021).

3.1.6 Campaign, operated by research institution or university in Oceania

One uncommon instance of a campaign-based sensor network with a live data dashboard is the Knowing Our Ambient Local Air-quality (KOALA) project at Queensland University of Technology in Australia (Queensland University of Technology, accessed 3/10/2024). KOALA offers measurements of CO and PM in a variety of locations, including deployments in Australia, China, Vietnam, Sri Lanka, and several islands in Oceania. Since this network is deployment based, not all regions of the map are active, and there is no historical archive for end users to download data from. However, as is typical of university-grade research projects, the KOALA monitors are calibrated both indoors and outdoors with a reference-grade instrument to ensure proper performance (Jayaratne et. al., 2021; Liu et. al., 2020; Kuhn et. al., 2021).

Another sensor campaign in the Oceania region used Aeroqual ozone sensors in Auckland, New Zealand, conducted by the University of Auckland (Miskell et. al., 2017). The same general framework and ozone sensors were also used in a study in British Columbia, Canada. An in-lab calibration scheme was utilized to apply simple linear corrections to the ozone data (Bart et. al., 2014) as well as an outdoor colocation with a reference-grade instrument, and field comparisons of individual sensors. Both studies aimed to establish best practices for deploying networked sensors, including the examination of intra- and inter-site differences, and the effects of local topography and meteorological conditions on sensor readings.

3.1.7 Campaign, operated by research institution or university in Africa

In Africa, we encountered numerous studies using low-cost sensors to monitor PM (Singh et. al., 2021; Abera et. al., 2020; Tékouabou et. al., 2022; Pope et. al., 2018; Raheja et. al., 2022; Hodoli et. al., 2023; Lassman et. al., 2020; Giordano et. al., 2021; Omokungbe et. al., 2020; Grych et. al., 2020; Gnamien et. al., 2021; Ngo et. al., 2019; Bainomugisha et. al., 2023; Ndamuzi et. al., 2023), but far fewer targeting gas phase compounds. One reason for this is the prevalence of cookstoves in

certain African countries, for which PM is a greater concern than any gaseous pollutant (Alexander et. al., 2018). The gas-phase sensor studies we reviewed were less likely to include robust calibration techniques than those of higher income regions.

580 Carnegie Mellon University's RAMP sensor network, described in more detail in sect. 3.1.1, has deployed five sensors in Cote d'lvoire and another four in Accra, Ghana, as part of their "Improving Air Quality in West Africa" project (Bahino et. al., 2021). These ongoing studies include colocation of several sensors with reference monitors for improved calibration.

In Nairobi, a team of researchers from Massachusetts Institute of Technology and their collaborators deployed a network of
585 in-house built sensors measuring NO, NO_2, SO_2, and PM. This study represents the first time that air quality at schools was studied in Nairobi, thus student and community engagement played a large role in the study. Since the gas sensors exhibited temperature dependencies, a temperature correction was used to ensure data quality. Despite the technical limitations of the sensors, in this context their data was sufficient to begin understanding the differences in air quality at the different schools studied (deSouza et. al., 2017).

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In Nigeria, one study deployed five low-cost sensors in a semi-urban environment to measure ambient NO, NO_2, CO, CO_2, O_3, and PM. Researchers from Obafemi Awolowo University did not specify any true calibration procedures in their manuscript, but did note previous colocations of the same brand of sensor used with reference-grade instruments in the UK by another research group. Overall, the study was able to examine spatial differences among the five test locations (Owoade et.
595 al., 2021). In another Nigerian study, researchers from the Federal University of Technology Nigeria used portable CO loggers to compare urban and rural pollution. Since a prefabricated monitor was used, no additional calibration or quality assurance were completed (Balogun et. al., 2014).

A Moroccan team from Abdelmalek Essaadi University created and deployed their own low-cost sensor node measuring CO_2,
600 NO_2, and meteorological data with the goal of creating an algorithm that estimated the air quality index (AQI) from the sensor inputs alone. No gas sensor calibrations were conducted as exact concentrations were not required for their intended purpose. The initial sensor node was successful in predicting the AQI, although the project does not appear to have been scaled up to include more nodes yet (Fahim et. al., 2023).

605 Due to the lack of gas-phase stationary outdoor monitoring studies in Africa, here we list a few related studies outside the scope of our review for further reading. We encountered a mobile monitoring low-cost sensor study of CO, CO_2, and PM in Senegal (Ngom et. al., 2018). Another study used low-cost sensors measuring CO_2, NO_2, O_3, and PM indoors in Nigeria (Adamu et. al., 2023). Although these studies do not fit precisely into our review, they still represent lower-cost methods of better understanding gas-phase compounds in Africa, which is severely understudied.

3.1.8 Campaign, operated by research institution or university in Central & South America

Similar to Africa, the extent of low-cost sensors in Central and South America is extremely limited compared to other regions. Since PM is typically a greater concern than gases in the global south (Carvalho, 2016), we encountered more sensor networks measuring PM in these areas (Tagle et. al., 2020; Jang and Jung, 2023; Lopez-Restrepo et. al., 2021; Gramsch et. al., 2020; Gramsch et. al., 2021; Candia et. al., 2018; Connerton et. al., 2023; Dirienzo et. al., 2023; Quintero et. al., 2023) than those measuring gas-phase compounds, although overall coverage is still sparse. A few mobile sensor studies are available for further reading on gas-phase coverage in Central and South America (Guevara et. al., 2010; Alvear-Puertas et. al., 2022).

Researchers at the University of Brazil performed in-lab calibrations and applied linear regressions to ensure the quality of their low-cost CO sensors before deploying them in the local area, including during the World Cup. Data was stored in WebGIS via ArcGIS software, allowing geographic data to be integrated with the CO data (Aguiar et. al., 2015). In Argentina, low-cost sensors measuring VOCs were deployed for agricultural monitoring by a team including several researchers from the Universidad Nacional de San Luis (Valenzuela et. al., 2018). While this preliminary study focused more on the creation of the sensor platform rather than its calibration or results, it shows promise for the growth of low-cost sensor networks in South America in the coming years.

AQMesh sensors, which are described in more detail in sect. 3.2, were deployed by the University of Leeds and local collaborators in Nicaragua for 6 months in 2017 downwind of the active Masaya volcano to monitor SO_2 and PM. Outdoor colocation with a reference-grade instrument was used to calibrate the sensor signals. Some nodes were more accurate than others in detecting volcanic emissions, but were suitable for identifying PM enhancements nonetheless (Whitty et. al., 2022). Other studies in Nicaragua and neighboring countries like Costa Rica have employed low-cost sensors onboard uncrewed aerial systems (UAS) (Xi et. al., 2016; Granados-Bolaños et. al., 2021) or other low-cost techniques (Aguilera et. al., 2020) to monitor volcanic plumes.

In Peru, sensors measuring CO, NO_2, SO_2, H_2S, O_3, CO_2, and PM were deployed at four outdoor locations by the Pontifical Catholic University of Peru. The research group built geographic data visualization into their interface, and compared measured concentrations among sensors as well as with a nearby government-run air quality monitoring station (David et. al., 2015).

In Cienfuegos, Cuba, a low-cost sensor measuring NO_2, SO_2, O_3, CO, and PM was deployed by researchers from Universidad Central "Marta Abreu" de Las Villas and collaborators, primarily for calibration and quality assessment purposes, including two laboratory calibrations and a month-long field deployment near a reference-grade monitor. We have included this calibration-focused study here due to the lack of gas-focused studies in this region, as well as the relevant local sources

surrounding the monitor placement, including an oil refinery, thermoelectric plant, charcoal production plant, and diesel-related sources (González Rivero et. al., 2023; Martinez et. al., 2023).

645 We also encountered two low-cost sensor network pilot studies in Ecuador by researchers at Universidad San Francisco de Quito USFQ and Universidad Técnica de Cotopaxi. One measured CO, CO_2, and PM in three distinct locations. A previous study by the same group conducted a chamber calibration test for the sensors (Guanochanga et. al., 2018). Researchers found that for their urban site in Quito, Ecuador, the average CO value was below the target given by the local government, but exceeded World Health Organization guidelines (Fuertes et. al., 2015).

650 **3.2 Campaign, operated by private companies**

Several sensor networks operated by private companies operate using campaign-based deployments. Typically, these companies have their own portals for data visualization and/or analysis, but unlike the quasi-permanent sensor network companies, this data is only available to users who purchase a sensor and a data management plan. These companies focus on targeted air quality solutions for their clients rather than widely available public data or citizen science. Since their full data
655 portals are typically only available on a subscription basis, we have opted to include them in the campaign category because widespread, long-term, stationary data is not publicly available at the time of writing. The data analysis included with the subscriptions is generally more advanced than those offered by public networks, including advanced calibration procedures and real-time modeling. MODULAIR and Bettair are the only two companies reviewed that directly address the effects of age on their sensors' performance. Peer-reviewed studies concerning the use of the sensor packages in this category tend to be
660 short-term deployments focusing on a specific point source or local phenomenon. These companies are usually headquartered in the US or Europe.

Airly requires its users to purchase a subscription to fully utilize their sensor packages. It is dually headquartered in both Poland and California, USA. Their target pollutants include CO, NO_2, O_3, SO_2, and PM (Airly Data Platform and Monitors,
665 accessed 9/18/2023). Airly's live map includes data from government-run monitoring stations in addition to its own sensors, notated by different shapes on the map. Historical data can be viewed on the map, but only represents the past 24 hours, and the end user needs to utilize the API to download it. The map also includes a forecast extending forward 24 hours. Airly's sensor calibration procedures are regularly performed, hence incentivizing customers to maintain their subscriptions. Sensors are calibrated in a laboratory setting followed by an outdoor colocation with a reference-grade instrument. Routine monitoring
670 of the sensor package once deployed is a unique aspect of Airly's model, including consideration of local environmental conditions and relevant satellite data to ensure sensor packages are performing adequately during deployment (Airly – Quality & Certificates, accessed 9/18/2023).

The MODULAIR sensor packages by QuantAQ measure CO, CO_2, NO, NO_2, O_3, and PM. Similar to Airly, users need to purchase access to the QuantAQ cloud to access their data and the API. Different pricing plans are offered for "basic", "pro", and "enterprise" users, the latter two of which include an annual inspection and re-calibration of the sensor, ensuring proper functioning and accuracy of the data. The details of this calibration process are not specified on their public-facing website as of 2023, but it appears that data transparency and calibration models are available to paid subscription users. Likewise, data visualization is available within the cloud for paid users, but has yet to be made publicly available for citizen science use (QuantAQ, accessed 9/18/2023). The MOULAIR sensors have been utilized in several peer-reviewed publications (Yang et. al., 2022; Prathibha et. al., 2020).

Another company attempting to address the limited longevity of its sensors is Barcelona-based Bettair. Rather than reeling its devices in yearly for recalibration, the company sells sensor "cartridges" that are meant to be repurchased every two years, ensuring that the sensors are easily replaced at the end of their useful lifetime without having to purchase an entirely new node. Each sensor package measures: CO, CO_2, NO, NO_2, O_3, SO_2, H_2S, and PM (Bettair Cities, accessed 9/18/2023). Colocation with reference-grade monitors shows strong agreement for NO, NO_2, and O_3 (Perello, 2018). Bettair offers a software platform for its users which includes mapping and other data visualization, but the data is not made publicly available. While the Bettair nodes can be implemented as stationary devices in future studies, to date, the only peer-reviewed studies utilizing them have adapted them as wearables (Kotzagianni et. al., 2023; Vrijheid et. al., 2021).

Kunak AIR, a company based in Spain, has deployed their sensor packages for CO, O_3, NO_x, SO_2 and PM in short-term campaigns globally, with notable deployments including Ethiopia, Germany, India, Belgium and Spain (Ibarrola, 2022; Hofman et. al., 2022; Saúco et. al., 2022). By opting into a paid software package called Kunak AIR Cloud, users unlock access to air quality reports, unspecified calibration and supervision of their sensors, and data visualization and analysis tools, including mapping and basic plotting features (Kunak AIR, accessed 9/18/2023). This company shares many characteristics of the quasi-permanent networks described previously, but we did not encounter any publicized long-term (2+ years) stationary deployments of Kunak sensors in our review.

AQMesh is a UK-based sensor package manufacturer which targets many common pollutants: CO, CO_2, NO, NO_2, O_3, SO_2, VOC, and PM in addition to less-commonly studied H_2S. Data portal and API access are only available to subscribers (AQMesh, accessed 9/18/2023). The AQMesh sensor packages have been used in a wide array of campaign-based research studies (Castell et. al., 2018; Jiao et. al., 2015; Rodríguez et. al., 2020). One study reported in 2017 that the sensors were not yet ready for research-grade applications (Castell et. al., 2017), zeroing in on the importance of proper calibration.

Ellona's WT1 electronic nose platform is one of the few sensor nodes studied here which is customizable from a long list of sensors, many of which are less frequently studied (including H_2S, NH_3, HCl, H_2O_2, HCHO, CH_4, and H_2) in addition to the

typical pollutant list: CO, CO_2, NO, NO_2, O_3, SO_2, VOCs, and PM. Similar to the other campaign-based sensor companies, its data processing, calibration, and visualization procedures are hidden behind a paywall for users only (Ellona, accessed 9/18/2023). At least one peer-reviewed study utilized the WT1 sensors for campaign-style research efforts as of September 2023 (Panzitta et. al., 2022). Ellona is based in France, and their website boasts usage in countries that appeared infrequently elsewhere in our review, including Estonia and Canada (Ellona Customer Cases, accessed 2/12/2024).

India-based Prana Air builds sensor packages offering a similar sensor range: CO, CO_2, NO, NO_2, O_3, SO_2, VOC, H_2S, NH_3, and PM. Sensor packages can be added to their AQI mobile app, which also includes data from regulatory monitoring stations. According to their website, the sensor packages are calibrated "distinctively" (Prana Air, accessed 9/18/2023). Studies using the Prana Air monitors seem to focus on PM (Patwardhan et. al., 2021; Kumar and Doss, 2023).

Oizom is another privately-owned sensor package company with offices in India and France. Their "Polludone" platform measures CO, CO_2, VOCs, and PM. The sensors include unspecified built-in calibrations and a software package, including live data monitoring and API options. Oizom sensors appear to be gaining international traction, with their website boasting usage of their products in more than 50 countries (Oizom, accessed 2/7/2023); peer-reviewed outdoor applications include traffic monitoring in Germany (Kurtenbach et. al., 2022) and emissions from fireworks in India (Shankar et. al., 2023).

Serbian company ekoNet manufactures sensors that measure CO, CO_2, NO, NO_2, O_3, SO_2, and PM. Like most of the companies in this category, web and app-based data visualization is limited to subscribers, with three different packages available: basic, standard, and advanced (ekoNet, accessed 9/18/2023). The ekoNet sensors have been utilized in several peer-reviewed publications to date (Vajs et. al., 2021; Jovašević-Stojanović et. al., 2015; Drajic et. al., 2020).

3.3 Campaign, operated by government

The two examples of campaign-style low-cost sensor deployments organized by government agencies listed in this section both consist of in-house built sensor packages deployed for the governing body to measure key pollutants in certain regions as well as to better understand the use of low-cost sensors themselves. These reports include calibration and data validation efforts such that the governing agency learned best practices to pass on to their constituents.

The US EPA has sponsored various low-cost sensor projects over the years. Its Village Green project focused on community outreach using low-cost sensor packages measuring O_3 and PM, later expanding to NO_2, VOCs, and black carbon. The project deployed these sensor packages campaign-style in a handful of US cities, including: Durham, North Carolina; Houston, Texas; Washington, DC; Kansas City, KS; Philadelphia, PA; Oklahoma City, OK; Hartford, CT; and Chicago, IL (US EPA Village Green Project, accessed 9/18/2023). Sensor data was compared with that of nearby regulatory grade monitors to ensure data quality (Jiao et. al., 2015).

The Italian government's ENEA (translated, Italian National Agency for New Technologies, Energy and Sustainable Economic Development) has likewise sponsored various network sensor efforts in recent years. During the RES-NOVAE (translated, Networks Buildings Streets: New Challenging Objectives for Environment and Energy) National Project, sensor packages designed and built by ENEA called AIRBOX were deployed in Bari, Italy to measure: CO, CO_2, NO_2, O_3, SO_2, VOCs, and PM, focusing on roadside emissions (Penza et. al., 2017). Early results comparing the sensors with nearby reference monitors were promising (Suriano et. al., 2016). ENEA's AIRBOX sensors have been used in a small number of other deployments (Borrego et. al., 2016). Another ENEA-built sensor package, NASUS, was designed to measure CO, NO_2, SO_2, H_2S, and PM in outdoor deployments, and proved effective in lab calibrations (Suriano et. al., 2014), outdoor colocations with reference instruments (Penza et. al., 2014), and during a deployment near a landfill (Penza et. al., 2015).

Table 2: Campaign Sensor Networks Reviewed and Selected Characteristics

Sensor Network	Organization Type	Location	Pollutants	Calibration Method(s)
Airly	Company	global	CO, NO_2, O_3, PM, SO_2	Lab calibration, Co-location with reference instrument
AirQino	Research Institution or University	Italy	CO, CO_2, NO_2	Co-location with reference instrument
AQMesh	Company	UK, Portugal, Nicaragua	CO, NO, NO_2, O_3	Co-location with reference instrument
ARISense	Research Institution or University, Company	Malawi, USA	CO, NO, NO_2, O_3, PM	Co-location with reference instrument
Beijing Sensors (Chinese Academy of Sciences)	Research Institution or University	China	CO, NO_2, O_3, SO_2	Co-location with reference instrument
Beijing Sensors (Tsinghua University)	Research Institution or University	China	CO_2, NO, NO_2, O_3, PM	Co-location with reference instrument
Bettair	Company	Spain	CO, CO_2, H_2S, NO, NO_2, O_3, PM, SO_2	Co-location with reference instrument
CairBox	Company	France	CH_3SH, H_2S	Co-location with reference instrument
CAPTOR Box	Research Institution or University	Spain, Italy, Austria	CO, CO_2, NO, NO_2, O_3	Co-location with reference instrument
CarboSense	Research Institution or University	Switzerland	CO_2	Co-location with reference instrument
CO in Brazil	Research Institution or University	Brazil	CO	Lab calibration
CO in Nigeria	Research Institution or University	Nigeria	CO	Not reported
CO in Taiwan	Research Institution or University	Taiiwan	CO	Co-location with reference instrument
Cuba Sensors	Research Institution or University	Cuba	CO, NO_2, O_3, PM, SO_2	Lab calibration, Co-location with reference instrument
ECN Airbox	Research Institution or University	Portugal	NO_2, O_3, PM	Co-location with reference instrument
Ecuador IoT Sensors	Research Institution or University	Ecuador	CO, CO_2, PM	Not reported
ekoNET	Company	Serbia	CO, CO_2, NO, NO_2, O_3, PM	Co-location with reference instrument
Ellona WT1	Company	France, Canada, Estonia, italy	CH_4, CO_2, H_2S, NH_3, NO_2, PM, VOC	Varies by end user
Envirowatch E-MOTEs	Research Institution or University	UK	CO, NO, NO_2	Co-location with reference instrument
India IoT Sensors	Research Institution or University	India	CO, PM	Not reported
INSTEP	Research Institution or University	USA	CH_4, CO, CO_2, HCHO, NO_2, O_3	Co-location with reference instrument
Israel CanarIT	Research Institution or University	Israel	NO_2, O_3, PM, VOC	Co-location with reference instrument
KOALA	Research Institution or University	Australia, China, Sri Lanka, Vietnam, Fiji	CO, PM	Co-location with reference instrument
Kunak Air	Company	Ethiopia, Germany, India, Belgium, Spain	CO, NO, NO_2, O_3, PM, SO_2	Co-location with reference instrument

MAS (mini air system)	Research Institution or University	China	CO, NO$_2$, PM	Co-location with reference instrument
MGMS (Multi-gas monitoring stations)	Research Institution or University	Qatar	CO, H$_2$S, NO, NO$_2$, O$_3$, PM, SO$_2$	Not reported
MODULAIR	Company	global	CO, CO$_2$, NO, NO$_2$, O$_3$, PM	Co-location with reference instrument
Morocco IoT Sensors	Research Institution or University	Morocco	CO$_2$, NO$_2$	Not reported
MPAQS (MultiPollutant Air Quality Sensor)	Research Institution or University	India	CO, NO$_2$, O$_3$, PM, SO$_2$	Co-location with reference instrument
Nairobi Sensors	Research Institution or University	Nairobi	NO, NO$_2$, PM, SO$_2$	Defer to sensor manufacturer
NASUS	Government	Italy	CO, H$_2$S, NO$_2$, SO$_2$	Lab calibration, Co-location with reference instrument
Nigeria Sensors	Research Institution or University	Nigeria	CO, CO$_2$, NO, NO$_2$, O$_3$, PM	Defer to sensor manufacturer
NO2 in Tokyo	Research Institution or University	Japan	NO$_2$	Lab calibration
O3 in New Zealand	Research Institution or University	New Zealand, Canada	O$_3$	Co-location with reference instrument
Oizum	Company	India, France	CO, CO$_2$, PM, VOC	Not reported, Varies by end user
PAS	Research Institution or University	China	NO, NO$_2$, O$_3$	Co-location with reference instrument
Peru Sensors	Research Institution or University	Peru	CO, CO$_2$, H$_2$S, O$_2$, O$_3$, NO$_2$, PM, SO$_2$	Co-location with reference instrument
Prana Air	Company	India	CO, CO$_2$, H$_2$S, NO$_2$, O$_3$, PM, SO$_2$	Not reported
RAMP (Real-time Affordable Multi-Pollutant)	Research Institution or University	USA, Puerto Rico, Africa, Canada	CO, CO$_2$, NO$_2$, O$_3$	Co-location with reference instrument
RES-NOVAE	Government	Italy	CO, CO$_2$, NO$_2$, O$_3$, PM, SO$_2$	Co-location with reference instrument
SATVAM	Research Institution or University	India	NO$_2$, O$_3$	Co-location with reference instrument
SNAQ boxes	Research Institution or University	UK, Nigeria, China, Portugal	CO, CO$_2$, NO, NO$_2$, PM, VOC	Co-location with reference instrument
SNUCO2M	Research Institution or University	South Korea	CO$_2$	Co-location with reference instrument
Trafficsensnet project	Research Institution or University	Czech Republic	CO, NO$_2$, PM, SO$_2$, VOC	Co-location with reference instrument
VIEW (Volunteer Internet-based Environment Watch)	Research Institution or University	Pakistan	CO, O$_3$, SO$_2$	Not reported
Village Green Project	Government	USA	NO$_2$, O$_3$, PM, VOC	Co-location with reference instrument
VOCs in Argentina	Research Institution or University	Argentina	VOC	Not reported
Y-Pods	Research Institution or University	USA, Mongolia	CH$_4$, CO, CO$_2$, NO$_2$, O$_3$	Co-location with reference instrument

4 Trends across Stationary Low-Cost Sensor Networks

780   The most commonly occurring gas-phase compounds to appear in our review of stationary gas-phase monitoring networks varied by deployment type. Even though we selected for gas-phase networks only, networks that also included PM dominated the quasi-permanent pollutant counts and were sizable in campaign-style deployments as well. NO_2, O_3, and CO were the most measured gas-phase pollutants for campaign networks. For quasi-permanent networks, O_3 was measured more than any other gas-phase compound, followed by CO_2 and VOCs. Lumping both total and speciated VOCs into one category brings the

785   number of VOC observations close to those of CO_2 in the quasi-permanent category, but the low numbers of VOCs in each study type highlights the need for more observations of these compounds, which are important in both human health and climate change contexts.

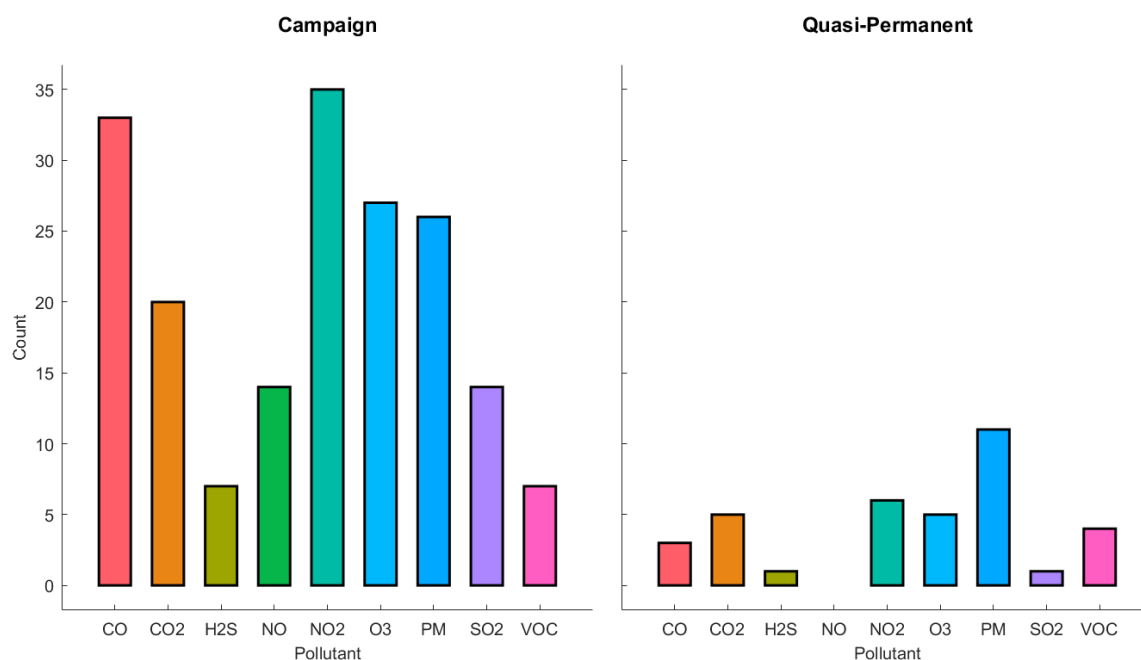



Figure 3: Histogram of pollutants in each selected sensor package. Note that a sensor package must measure at least one gas-phase
790   **compound to be included; no standalone PM sensors are listed here.**

    We also sought to characterize global coverage and biases in low-cost sensor placement by mapping the locations of each of the sensor networks studied. Note that for the campaign-based studies, we sought to include at least two networks from each geographic area, although some regions (North America and Europe) were much easier to find information on than others (the

795   Middle East, Central and South America, Oceania), which is reflected in Fig. 4. In the regions with sparser sensor sampling, the networks also tended to be smaller in scale with less longevity compared to more commonly sampled regions; we

encountered networks with few nodes, and more standalone studies as opposed to multiple deployments of the same sensor packages.

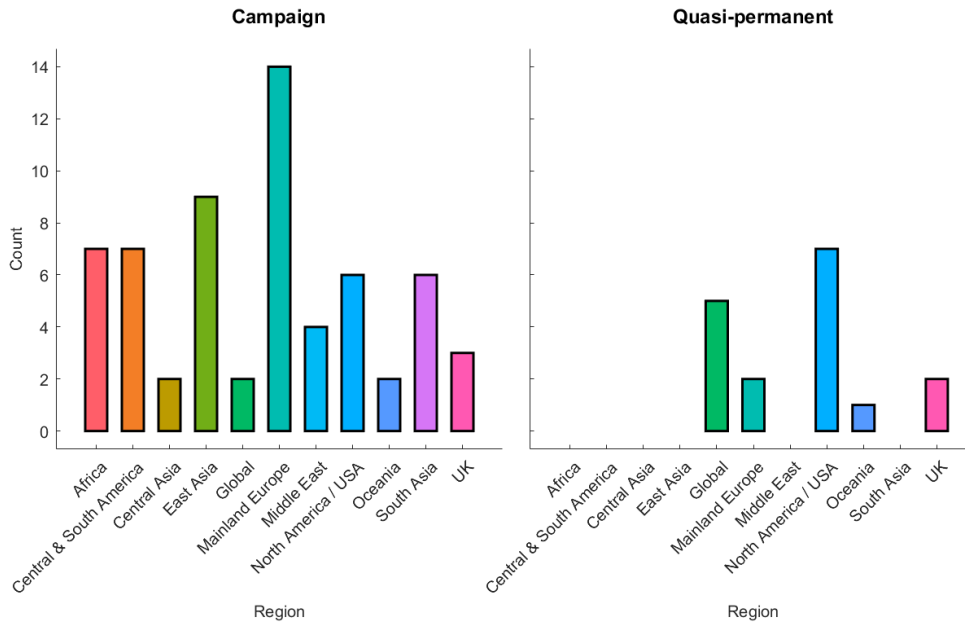
800   For the quasi-permanent networks, the vast majority were either US-based or featured global coverage, although most of the networks with global coverage had their headquarters based in the US. Overall, we found that monitors are concentrated in the northern hemisphere mid-latitudes, in high and some middle-income countries, in urban areas. Ironically, low-cost sensors are an attractive solution to this bias in monitoring locations, but clearly, more needs to be done, perhaps by local governments or even sensor companies themselves, to get the technology into less commonly studied areas.

805

Figure 4: Histogram of locations of sensor studies, split into broad geographic regions.

Since one of the biggest issues plaguing low-cost sensor usage is data quality, we also sorted each of the networks we reviewed by their calibration method, as shown in Fig. 5. Most sensor networks reviewed relied on colocation of the sensors with a reference-grade instrument, making this the gold standard for sensor calibration. However, it is important to note that this

810   category is extremely broad, and that variations in the implementation of colocations can still affect sensor data quality considerably.

For instance, some networks may only colocate one of their sensors with the reference instrument (e.g. Love my Air Denver), which does not consider variations among individual sensors. Others that colocate their sensors with a reference instrument

815   may do so as more of a quality check than a true calibration; a sensor is considered "good enough" if concentrations between sensor and reference instrument do not deviate beyond a set range. The most robust in this category are sensor networks that

use this colocation period to derive calibration algorithms, ensuring that the sensor data are as close to the reference data as possible. Even within the algorithm category, some networks may use a single correction factor, while others will use machine learning or other more sophisticated methods to achieve the best fit possible (e.g. Y-pods).

820   There is also a time component to sensor calibrations due to both sensor age and seasonality. Sensor performance tends to decline as they age (Rai et. al., 2017), with most sensors' useful life hovering around approximately two years (Okorn et. al., 2021). Beyond this point, their performance may become less reliable, and drift may become evident in the signals. Likewise, low-cost sensors can be very sensitive to environmental conditions, including temperature, pressure, and humidity (Okorn et. al., 2021), so a calibration conducted in hot, humid summer weather may not translate well to cold, dry winter conditions

825   experienced at the same location during different times of year. Thus, these broad-brush categories do not control for the frequency of calibration, nor the robustness of the comparison or algorithm.

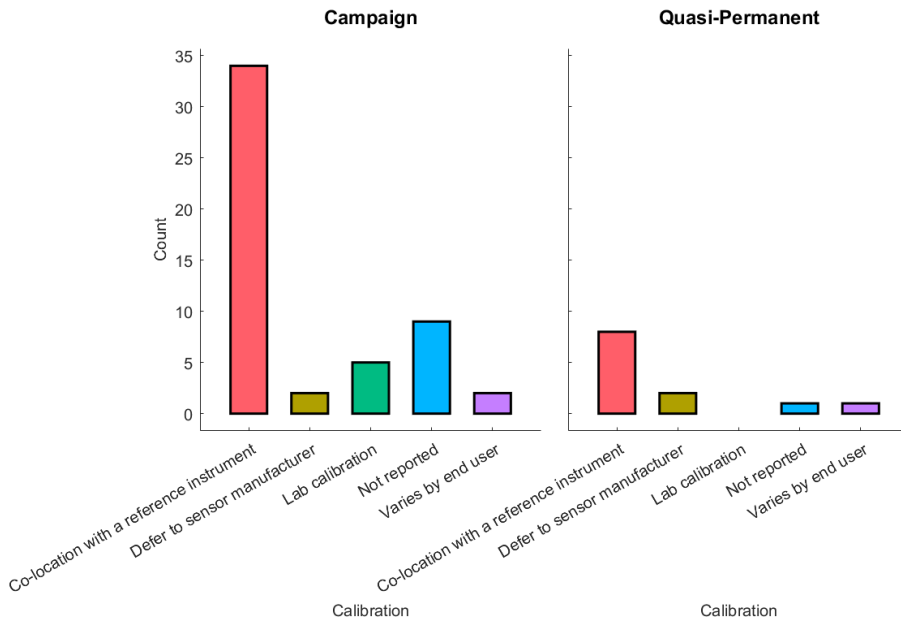



Figure 5: Histogram of sensor network calibration methods.

The networks included in the "not reported" calibration category did not provide specific information on their calibration

830   techniques in publications or on their websites at the time of this review. Note that the researchers may have chosen to withhold details for proprietary reasons, in the case of private companies, or may not have performed any calibration on their sensors. In either case, we did not have sufficient information to categorize their techniques into any other category. The "varies by end user" category implies just that: we found several groups employing the sensors in both campaign and quasi-permanent structures, with each group choosing their own calibration scheme for the same sensor. Likewise, several groups in each

835   category pointed back to materials on the sensor's effectiveness as reported by the manufacturer in lieu of conducting their own calibration. Again, due to the environmental dependence of low-cost sensors, outdoor colocations are crucial for

understanding how the sensor will respond in its deployment environment, which all other calibration methods are deficient in.

840   On a related note, data quality does not necessitate data availability. The highest quality sensor data, calibrated via colocation with subsequent fitting algorithms, are most likely to hail from university or research groups, which are also the least likely to ensure public data access. While most data collected by these groups is available upon request, end users outside the scientific community are less likely to know where to look for data that is not available in a public repository.

5 Sensor Network Unification Efforts

845   In the wake of the abundance of sensor networks springing up worldwide, several websites and databases have emerged in attempts to highlight noteworthy efforts in the space and make it easier for sensor users and potential data end users to find sensor networks and data that matches their needs. Most of the sensor unification efforts we studied included lists of sensor networks with links to their individual websites. Several others include an interface for data visualization – typically a map with pins for each sensor node, with different colors corresponding to different concentration ranges. These may also include

850   a data download or API option, but none of the sensor network unification efforts we studied include specifics on data quality broken down by each sensor type.

As discussed in the previous sections, calibrations are not created equal among sensor networks; while some include vigorous, frequent calibration procedures, others are seldom calibrated, if at all. Sensor synthesis efforts could be made stronger with

855   more emphasis on data quality, ensuring that the end user understands the uncertainty of the reported values. Furthermore, having a standard data format and download option would make it easier for users outside the scientific community to access, combine, and analyze data that might be relevant to them. Below, we describe several examples of data unification projects, highlighting both their strengths and limitations.

860   Several of the long-term monitoring networks discussed in sect. 2 operate de facto data unification products, with their data maps including data from multiple low-cost sensor networks and regulatory monitors (e.g. AirNow's Fire & Smoke Map, Clarity, Tellus). These data unification efforts to date have broadly overlooked the low-cost sensor networks established by university and other small-scale research groups, focusing instead on other companies or non-profit organizations. However, it is precisely this smaller scale that allows sensor researchers in this space to develop state-of-the-art calibration procedures;

865   academic institutions tend to have the highest degree of certainty and calibration in their data (see sects. 2.3 and 3.1).

Beyond these, there are a small number of projects that aim to highlight data from a variety of different sensor networks. The Clean Air Monitoring and Solutions Network (CAMS-Net) is an NSF-funded project which aims to create a "network of

networks", making air quality data from a variety of sources publicly accessible in one digital space, with a focus on low-cost

870   sensors. As of 2023, their website hosts an extensive list of participating networks, but does not yet have a large, publicly

available data repository (CAMS-Net, accessed 9/18/2023). OpenAQ is a non-profit organization that similarly aims to unify

air quality sensor data, including an interactive map and API for data downloads (OpenAQ, accessed 9/18/2023). RIVM, a

government division in the Netherlands, has created a data portal dubbed "Measuring Together" where citizen scientists can

upload their low-cost sensor data (Wesseling et. al., 2019).

875

Another major player in the sensor network unification space is the World Air Quality Index, which operates as a non-profit

organization (Real-time Air Quality Sensor Networks, accessed 1/11/2024). The site's strengths include live mapping, basic

plotting, a link to the network's own website, and an option to download historical data. For users wanting to add their own

data to the site, it encourages the use of GAIA sensors, which are PM focused, with the option to add a CO_2 sensor only for an

880   additional cost. However, it also supports data from other sensor manufacturers and networks. Like the other sensor unification

projects, end users wanting more detailed information about each network will need to follow links, which sometimes direct

the user to information on the deployment location rather than the sensor network itself. For instance, a sensor deployed on

the roof of an embassy might link to the embassy's website regardless of whether the embassy or a third party was responsible

for the deployment and upkeep of the sensor, leaving the user with little additional information. Likewise, multiple different

885   sensor networks may be represented on an individual sub-map, which can make determining the source of data difficult. For

users who are merely interested in the data at face value or want to understand how many monitors are already present in a

certain area, tools like this are immensely helpful in mapping current sensor efforts. However, more advanced end users who

want to understand the measurement and calibration techniques behind each sensor should expect to do a lot more digging to

find this information.

890

We categorize these projects combining sensor data from a variety of sources in a list or map format as sensor unification

focused, making it possible for end users to locate real-time or historical data that may be personally relevant. While these

projects can be useful, sensor harmonization should be the next step in increasing the usefulness of sensor data from a variety

of networks. Data "harmonization" as used here follows the intent of Zeb et. al. (2021) of "reconciling various types, levels

895   and sources of data in formats that are compatible and comparable, and thus useful for better decision-making" and the

principles of Cheng et. al. (2024). In the context of low-cost sensors, harmonization includes taking additional steps to ensure

the seamless use of data: simple enough for citizen scientists to access it, yet quality-assured for scientists and other advanced

users. This is no small task, but steps in this direction might include a common download format for sensor data, availability

of both live and historical data, and information on data quality or calibration procedures. Sensor data harmonization projects

900   could take sensor unification efforts to the next level by making sensor data more practical for scientific use. One recent

example of a call for data harmonization is Schneider et. al.'s 2019 scientific opinion piece, which aims to create standard

terminology for processed low-cost sensor data, ranging from raw measurements (level 0) to data that has been corrected using

nearby reference stations and/or measured environmental parameters (level 2A-B). The highest prescribed level (4) describes spatially continuous maps derived from sensor data, including assimilation into models. The authors state that these levels will provide end users with improved data integrity and transparency without requiring researchers to disclose proprietary calibration algorithms.

6 Emerging and Future Sensor Directions

In the most recent low-cost sensor studies (spanning from approximately 2020 to present), an emerging trend is incorporating sensors into larger scale modeling. Many of the application-based projects included in our review tend to view each sensor data point as individual, e.g. for discerning air quality at a specific point in space and time, typically for comparative purposes with other sensor nodes. In more recent studies, however, we encountered many more applications into geospatial interpolation models such as kriging across sensor nodes to estimate pollutant concentrations not only at sensor locations, but between them in an even finer grid (Lee et. al., 2024; Liu et. al., 2022; Nori-Sarma et. al., 2020).

While low-cost sensors have long been implemented as a solution to gaps in traditional air quality monitoring techniques, only more recently have they been used to complement other monitoring efforts via data fusion techniques. In these kinds of studies, low-cost sensor measurements are typically coupled with a combination of regulatory monitoring, satellite data, and model outputs, with different weights assigned to each data stream according to the estimated data quality (Yoo et. al., 2020; Bobbia et. al., 2022; Gressent et. al., 2020; Liang et. al., 2023; Li et. al., 2020; Dewage et. al., 2024). Including low-cost sensor data in these models can improve forecasting (Malings et. al., 2021).

A smaller number of studies we found noteworthy utilize low-cost sensors to estimate pollutant flux across a region, since finely spaced sensors can essentially act as a grid to estimate across (Turner et. al., 2020). Low-cost gas sensors have also been used in flux chambers to aid evaluation efforts (Bastviken et. al., 2020). Overall, we expect to see the point-source and general monitoring efforts described in sects. 2 and 3 continue to flourish in the next decade. Further evolution of these approaches and advanced modeling-based studies will require improvement in data quality and spatial coverage of trace gas sensing networks.

Current and emerging sensor directions for non-stationary deployments include the increased use of air quality sensors on uncrewed aerial vehicles (UAV), which can afford air quality monitoring in previously inaccessible areas. Common applications in this area include: measuring emissions from wildfires (Bushnaq et. al., 2021; Afghah et. al., 2019; Mo et. al., 2021), measuring emissions from volcanoes (Villa et. al., 2016; Granados-Bolaños et. al., 2021; Xi et. al., 2016), and gas leak detection (Pochwala et. al., 2020; Liu et. al., 2021; Sonkar et. al., 2022). Mobile sensors have also been deployed indoors on ships (Schalm et. al., 2022; Metreveli 2021), and complementary stationary deployments at ports are helping to assess

935   emissions and the influence of maritime meteorology on air quality (Jayaratne et. al., 2020; Zhou et. al., 2022; Gagic et. al., 2022).

7 Conclusions

Particulate matter is the most frequently studied pollutant using low-cost sensors. In regions with sparse gas-phase sensor data, we could always find several examples reporting particulate matter. Even among the gas-phase networks studied here, most
940   multi-pollutant sensor packages also included a PM sensor, especially among the largest networks. Despite the surge of low-cost sensor networks in the past decade, more monitoring is needed to better address air quality concerns and disparities on global and regional scales. At present, Central and South America, the Middle East, and Africa are especially lacking. Although larger networks such as PurpleAir service these areas, coverage is significantly less dense compared to the US and western Europe. Even in countries with higher spatial coverage of sensors, rural areas lack the same coverage as their urban
945   counterparts, and countries with higher gross domestic product tend to have more sensors – the differences between western and eastern Europe are a prime example. Less wealthy and more rural areas tend to have more regulatory monitoring gaps; closing the gap with well-calibrated low-cost sensors is an important first step toward adequate monitoring in underserved areas. Likewise, satellite and model-derived projections of climate-related impacts will be improved by well-calibrated, globally distributed, high-density surface observations of trace gases, particularly in regions with regulatory monitoring gaps.
950   Forward progress on complicated issues of human health and environmental justice will require significant expansion of the spatial coverage of hydrocarbon trace gas sensors, particularly with attention to detection of specific toxic compounds.

Data quality and availability also plague the use of low-cost sensors. This review found that the highest quality sensor data is obtained by utilizing an outdoor colocation with a reference instrument and subsequent algorithm development to ensure a
955   proper fit. While most campaign and quasi-permanent sensor networks alike rely on a colocation approach, university-based and other research groups typically remain the highest quality. One reason for this is their "gold-standard" post colocation algorithms, which bring the response of the sensors closer to the true value observed during the colocation period. Another strength of university-based projects is the smaller number of nodes usually deployed; the larger the network, and the more area covered, the less likely that every node has been properly calibrated.
960

However, data from research-focused networks is typically the hardest to access, with very few publicly available data portals. Most is available by request only and lacks a standard format, making it inaccessible for most citizen science or education outreach purposes. In contrast, many privately owned sensor companies, particularly in the quasi-permanent category, make their dataset publicly available, despite lacking these rigorous calibration procedures. Research-grade end users have largely
965   deemed global or country-wide calibrations inadequate, especially during wildfires or other extreme weather events.

Addressing sensor deployment gaps in trace gases and global spatial coverage, and sensor data gaps in quality and availability will ensure that low-cost sensors remain a valuable tool for decades to come.

Code Availability

The figures in this manuscript were created using the gramm package for MATLAB (Morel, 2018); contact the corresponding author for access.

Data Availability

For additional sensor network metrics, contact the corresponding author or the network directly.

Author Contributions

Kristen Okorn: Conceptualization; data curation; formal analysis; writing – original draft preparation
Laura T. Iraci: Conceptualization; writing – review & editing

Competing Interests

The authors declare that they have no conflict of interest.

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References

Abera, A., Mattisson, K., Eriksson, A., Ahlberg, E., Sahilu, G., Mengistie, B., Bayih, A. G., Aseffaa, A., Malmqvist, E., & Isaxon, C: Air pollution measurements and land-use regression in urban sub-Saharan Africa using low-cost sensors—Possibilities and pitfalls. Atmosphere, 11(12), 1357. https://doi.org/10.3390/atmos11121357, 2020.

Adamu, A., Arifalo, K. M., & Abulude, F. O.: Indoor air quality assessment using a low-cost sensor: A case study in ikere-ekiti, nigeria. Engineering Proceedings, 58(1), 42. https://doi.org/10.3390/ecsa-10-16021, 2023.

Afghah, F., Razi, A., Chakareski, J., Ashdown, J.: Wildfire Monitoring in Remote Areas using Autonomous Unmanned Aerial Vehicles. IEEE INFOCOM 2019 - IEEE Conference on Computer Communications Workshops, 835-840. 10.1109/INFCOMW.2019.8845309, 2019.

Agrawal, G., Mohan, D., & Rahman, H.: Ambient air pollution in selected small cities in India: Observed trends and future challenges. IATSS Research, 45(1), 19–30. https://doi.org/10.1016/j.iatssr.2021.03.004, 2021.

AGU Fall Meeting 2022: https://www.agu.org/fall-meeting-2022, last access: 17 September 2023.

Aguiar, E. F. K., Roig, H. L., Mancini, L. H., & Carvalho, E. N. C. B. de.: Low-cost sensors calibration for monitoring air quality in the federal district—Brazil. Journal of Environmental Protection, 06(02), 173. https://doi.org/10.4236/jep.2015.62019, 2015.

Aguilera, F., Layana, S., Rojas, F., Arratia, P., Wilkes, T. C., González, C., Inostroza, M., McGonigle, A. J. S., Pering, T. D., & Ureta, G.: First measurements of gas flux with a low-cost smartphone sensor-based UV camera on the volcanoes of northern chile. Remote Sensing, 12(13), 2122. https://doi.org/10.3390/rs12132122, 2020.

Air matters: https://air-matters.com/, last access: 10 March 2024

Air quality sensors: https://www.pscleanair.gov/539/Air-Quality-Sensors#:~:text=One%20of%20the%20most%20popular,regulatory%20monitors%20and%20comparing%20measurements, last access: 17 September 2023.

Air quality software for data analysis | Kunak AIR Cloud: http://kunakair.com/air-quality-software/, last access: 10 March 2024.

Aircare—Free air quality & pollen tracking app: https://getaircare.com/, last access: 10 March 2024.

AirGradient: https://www.airgradient.com/, last access: 26 August 2024.

Airly data platform and monitors: https://airly.org/en/, last access: 10 March 2024.

Airly—Quality & certificates: https://airly.org/en/features/quality-and-certificates/, last access: 10 March 2024.

Airnow: https://www.airnow.gov/, last access: 10 March 2024.

Airnow fire and smoke map: https://fire.airnow.gov/, last access: 10 March 2024.

Airnow fire and smoke map: Getting started: document.airnow.gov/airnow-fire-and-smoke-map-getting-started.pdf, last access: 10 March 2024.

Airu: https://airu.coe.utah.edu/, last access: 9 March 2024.

AirView Map by TELLUS: https://airview.tellusensors.com/, last access: 17 September 2023.

Airwatchstl: https://airwatchstl.mcustlouis.org/, last access: 9 March 2024.

1015 Alexander, D. A., Northcross, A., Karrison, T., Morhasson-Bello, O., Wilson, N., Atalabi, O. M., Dutta, A., Adu, D., Ibigbami, T., Olamijulo, J., Adepoju, D., Ojengbede, O., & Olopade, C. O.: Pregnancy outcomes and ethanol cook stove intervention: A randomized-controlled trial in Ibadan, Nigeria. Environment International, 111, 152–163. https://doi.org/10.1016/j.envint.2017.11.021, 2018.

Alford, K. L., & Kumar, N.: Pulmonary health effects of indoor volatile organic compounds—A meta-analysis. International

1020 Journal of Environmental Research and Public Health, 18(4), 1578. https://doi.org/10.3390/ijerph18041578, 2021.

Al-Hajjaji, K., Ezzin, M., Khamdan, H., Hassani, A. E., & Zorba, N.: Design, development and evaluation of a uav to study air quality in qatar (arXiv:1709.05628). arXiv. https://doi.org/10.48550/arXiv.1709.05628, 2017.

Alvear-Puertas, V. E., Burbano-Prado, Y. A., Rosero-Montalvo, P. D., Tözün, P., Marcillo, F., & Hernandez, W.: Smart and portable air-quality monitoring IOT low-cost devices in Ibarra city, Ecuador. Sensors, 22(18), 7015.

1025 https://doi.org/10.3390/s22187015, 2022.

Amegah, A. K.: Proliferation of low-cost sensors. What prospects for air pollution epidemiologic research in Sub-Saharan Africa? Environmental Pollution, 241, 1132–1137. https://doi.org/10.1016/j.envpol.2018.06.044, 2018.

Aqmesh: https://aqmesh.com, last access: 1 September 2024.

Arnold, C., Harms, M., & Goschnick, J.: Air quality monitoring and fire detection with the Karlsruhe electronic micronose

1030 KAMINA. IEEE Sensors Journal, 2(3), 179–188. https://doi.org/10.1109/JSEN.2002.800681, 2002.

Awokola, B. I., Okello, G., Mortimer, K. J., Jewell, C. P., Erhart, A., & Semple, S.: Measuring air quality for advocacy in africa (Ma3): Feasibility and practicality of longitudinal ambient PM2.5 measurement using low-cost sensors. International Journal of Environmental Research and Public Health, 17(19), 7243. https://doi.org/10.3390/ijerph17197243, 2020.

Awokola, B., Okello, G., Johnson, O., Dobson, R., Ouédraogo, A. R., Dibba, B., Ngahane, M., Ndukwu, C., Agunwa, C.,

1035 Marangu, D., Lawin, H., Ogugua, I., Eze, J., Nwosu, N., Ofiaeli, O., Ubuane, P., Osman, R., Awokola, E., Erhart, A., …

Semple, S.: Longitudinal ambient PM2.5 measurement at fifteen locations in eight sub-Saharan African countries using low-cost sensors. Atmosphere, 13(10), 1593. https://doi.org/10.3390/atmos13101593, 2022.

Badura, M., Batog, P., Drzeniecka-Osiadacz, A., & Modzel, P.: Low- and medium-cost sensors for tropospheric ozone monitoring—Results of an evaluation study in Wrocław, Poland. Atmosphere, 13(4), 542.

1040   https://doi.org/10.3390/atmos13040542, 2022.

Bahino, J., Giordano, M., Yoboué, V., Ochou, A., Galy-Lacaux, C., Liousse, C., Amegah, K., Hugues, A., Nimo, J., Beekmann, M., & Subramanian, R.: MOPGA/Improving Air Quality in West Africa: Low-cost sensors as a solution to improve the understanding of spatial and temporal variability in urban air pollution. EGU21-8210. https://doi.org/10.5194/egusphere-egu21-8210, 2021.

1045   Bainomugisha, E., Ssematimba, J., & Okure, D.: Design considerations for a distributed low-cost air quality sensing system for urban environments in low-resource settings. Atmosphere, 14(2), 354. https://doi.org/10.3390/atmos14020354, 2023.

Bales, E., Nikzad, N., Quick, N., Ziftci, C., Patrick, K., & Griswold, W.: CitiSense: Mobile air quality sensing for individuals and communities. Design and deployment of the CitiSense mobile air-quality system. Proceedings of the 6th International Conference on Pervasive Computing Technologies for Healthcare. 6th International Conference on Pervasive Computing

1050   Technologies for Healthcare, San Diego, United States. https://doi.org/10.4108/icst.pervasivehealth.2012.248724, 2012.

Balogun, I. A., Balogun, A. A., & Adegoke, J.: Carbon monoxide concentration monitoring in Akure—A comparison between urban and rural environment. Journal of Environmental Protection, https://doi.org/10.4236/jep.2014.54030, 2014.

Barcelo-Ordinas, J. M., Ferrer-Cid, P., Garcia-Vidal, J., Ripoll, A., & Viana, M.: Distributed multi-scale calibration of low-cost ozone sensors in wireless sensor networks. Sensors, 19(11), 2503. https://doi.org/10.3390/s19112503, 2019.

1055   Barcelo-Ordinas, J. M., Ferrer-Cid, P., Garcia-Vidal, J., Viana, M., & Ripoll, A.: H2020 project CAPTOR dataset: Raw data collected by low-cost MOx ozone sensors in a real air pollution monitoring network. Data in Brief, 36, 107127. https://doi.org/10.1016/j.dib.2021.107127, 2021.

Barkjohn, K. K., Gantt, B., & Clements, A. L.: Development and Application of a United States wide correction for PM_{2.5} data collected with the PurpleAir sensor [Preprint]. Aerosols/In Situ

1060   Measurement/Validation and Intercomparisons. https://doi.org/10.5194/amt-2020-413, 2020.

Barkjohn, K. K., Holder, A. L., Frederick, S. G., & Clements, A. L.: Correction and accuracy of PurpleAir PM2.5 measurements for extreme wildfire smoke. Sensors, 22(24), 9669. https://doi.org/10.3390/s22249669, 2022.

Barot, V., Kapadia, V., & Pandya, S.: QOS enabled IOT based low cost air quality monitoring system with power consumption optimization. Cybernetics and Information Technologies, 20(2), 122–140. https://doi.org/10.2478/cait-2020-0021, 2020.

1065 Bart, M., Williams, D. E., Ainslie, B., McKendry, I., Salmond, J., Grange, S. K., Alavi-Shoshtari, M., Steyn, D., & Henshaw, G. S.: High density ozone monitoring using gas sensitive semi-conductor sensors in the lower Fraser Valley, British Columbia. Environmental Science & Technology, 48(7), 3970–3977. https://doi.org/10.1021/es404610t, 2014.

Bastviken, D., Nygren, J., Schenk, J., Parellada Massana, R., & Duc, N. T.: Technical note: Facilitating the use of low-cost methane (CH_4) sensors in flux chambers – calibration, data processing, and an open-source make-

1070 it-yourself logger. Biogeosciences, 17(13), 3659–3667. https://doi.org/10.5194/bg-17-3659-2020, 2020.

BEACO2N: http://beacon.berkeley.edu/, last access: 10 March 2024.

Becnel, T., & Gaillardon, P.-E.: A deep learning approach to sensor fusion inference at the edge. 2021 Design, Automation & Test in Europe Conference & Exhibition (DATE), 1420–1425. https://doi.org/10.23919/DATE51398.2021.9474178, 2021.

Becnel, T., Sayahi, T., Kelly, K., & Gaillardon, P.-E.: A recursive approach to partially blind calibration of a pollution sensor

1075 network. 2019 IEEE International Conference on Embedded Software and Systems (ICESS), 1–8. https://doi.org/10.1109/ICESS.2019.8782523, 2019.

Becnel, T., Tingey, K., Whitaker, J., Sayahi, T., Lê, K., Goffin, P., Butterfield, A., Kelly, K., & Gaillardon, P.-E.: A distributed low-cost pollution monitoring platform. IEEE Internet of Things Journal, 6(6), 10738–10748. https://doi.org/10.1109/JIOT.2019.2941374, 2019.

1080 Bettair cities: https://bettaircities.com/, last access: 10 March 2024.

Bittner, A. S., Cross, E. S., Hagan, D. H., Malings, C., Lipsky, E., & Grieshop, A. P.: Performance characterization of low-cost air quality sensors for off-grid deployment in rural Malawi. Atmospheric Measurement Techniques, 15(11), 3353–3376. https://doi.org/10.5194/amt-15-3353-2022, 2022.

BKH Outdoor Sensor Network - Washington University in St. Louis: https://sites.wustl.edu/mongoliaproject/bkh-outdoor-

1085 network/, last access: 10 March 2024.

Bobbia, M., Poggi, J., & Portier, B.: Spatial correction of low-cost sensors observations for fusion of air quality measurements. Applied Stochastic Models in Business and Industry, 38(5), 766–786. https://doi.org/10.1002/asmb.2713, 2022.

Borrego, C., Costa, A. M., Ginja, J., Amorim, M., Coutinho, M., Karatzas, K., Sioumis, Th., Katsifarakis, N., Konstantinidis, K.,

1090   De Vito, S., Esposito, E., Smith, P., André, N., Gérard, P., Francis, L. A., Castell, N., Schneider, P., Viana, M., Minguillón, M. C., … Penza, M.: Assessment of air quality microsensors versus reference methods: The EuNetAir joint exercise. Atmospheric Environment, 147, 246–263. https://doi.org/10.1016/j.atmosenv.2016.09.050, 2016.

Brauer, M., Guttikunda, S. K., K a, N., Dey, S., Tripathi, S. N., Weagle, C., & Martin, R. V.: Examination of monitoring approaches for ambient air pollution: A case study for India. Atmospheric Environment, 216, 116940.

1095   https://doi.org/10.1016/j.atmosenv.2019.116940, 2019.

Brilli, L., Berton, A., Carotenuto, F., Gioli, B., Gualtieri, G., Martelli, F., Profeti, S., Trombi, G., Dibari, C., Moriondo, M., Vagnoli, C., & Zaldei, A.: Innovative low-cost air quality stations as a supporting means for road traffic regulations in urban areas. IOP Conference Series: Earth and Environmental Science, 489(1), 012023. https://doi.org/10.1088/1755-1315/489/1/012023, 2020.

1100 Brilli, L., Carotenuto, F., Gioli, B., Berton, A., Profeti, S., Gualtieri, G., Andreini, B. P., Stefanelli, M., Martelli, F., Vagnoli, C., & Zaldei, A.: An integrated low-cost monitoring platform to assess air quality over large areas. In K. Arai, S. Kapoor, & R. Bhatia (Eds.), Proceedings of the Future Technologies Conference (FTC) 2020, Volume 2(pp. 965–975). Springer International Publishing. https://doi.org/10.1007/978-3-030-63089-8_63, 2021.

Brynda, P., Honzík, P., Kosová, Z., & Šimonová, K.: Experience from the pilot project of the air quality sensor network in

1105   Litoměřice. 2020 Smart City Symposium Prague (SCSP), 1–6. https://doi.org/10.1109/SCSP49987.2020.9133785, 2020.

Brynda, P., Kopřiva, J., & Horák, M.: Trafficsensnet sensor network for measuring emissions from transportation. Procedia Engineering, 120, 902–907. https://doi.org/10.1016/j.proeng.2015.08.781, 2015.

Brynda, P., Kosová, Z., & Kopřiva, J.: Mobile sensor unit for online air quality monitoring. 2016 Smart Cities Symposium Prague (SCSP), 1–4. https://doi.org/10.1109/SCSP.2016.7501028, 2016.

Brzeziński, M., Sałach, K., & Wroński, M.: Wealth inequality in Central and Eastern Europe: Evidence from household survey and rich lists' data combined [*]. Economics of Transition and Institutional Change, 28(4), 637–660. https://doi.org/10.1111/ecot.12257, 2020.

Bushnaq, O.M., Chaaban, A., Al-Naffouri, T.: The Role of UAV-IoT Networks in Future Wildfire Detection. IEEE Internet of Things Journal, 8, 23(01). 10.1109/JIOT.2021.3077593, 2021.

Campmier, M. J., Gingrich, J., Singh, S., Baig, N., Gani, S., Upadhya, A., Agrawal, P., Kushwaha, M., Mishra, H. R., Pillarisetti, A., Vakacherla, S., Pathak, R. K., & Apte, J. S.: Seasonally optimized calibrations improve low-cost sensor performance: Long-term field evaluation of PurpleAir sensors in urban and rural India. Atmospheric Measurement Techniques, 16(19), 4357–4374. https://doi.org/10.5194/amt-16-4357-2023, 2023.

Camprodon, G., González, Ó., Barberán, V., Pérez, M., Smári, V., de Heras, M. Á., & Bizzotto, A.: Smart Citizen Kit and Station: An open environmental monitoring system for citizen participation and scientific experimentation. HardwareX, 6, e00070. https://doi.org/10.1016/j.ohx.2019.e00070, 2019.

Clean Air Monitoring and Solutions Network (CAMS-Net): https://camsnet.org/, last access: 10 March 2024.

Candia, A., Represa, S. N., Giuliani, D., Luengo, M. Á., Porta, A. A., & Marrone, L. A.: Solutions for SmartCities: Proposal of a monitoring system of air quality based on a LoRaWAN network with low-cost sensors. 2018 Congreso Argentino de Ciencias de La Informática y Desarrollos de Investigación (CACIDI), 1–6. https://doi.org/10.1109/CACIDI.2018.8584183, 2018.

Čapek, S.: The "environmental justice" frame: A conceptual discussion and an application. Social Problems, 40(1), 5–24. https://doi.org/10.2307/3097023, 1993.

Carotenuto, F., Bisignano, A., Brilli, L., Gualtieri, G., & Giovannini, L.: Low-cost air quality monitoring networks for long-term field campaigns: A review. Meteorological Applications, 30(6), e2161. https://doi.org/10.1002/met.2161, 2023.

Carotenuto, F., Brilli, L., Gioli, B., Gualtieri, G., Vagnoli, C., Mazzola, M., Viola, A. P., Vitale, V., Severi, M., Traversi, R., & Zaldei, A.: Long-term performance assessment of low-cost atmospheric sensors in the arctic environment. Sensors, 20(7), 1919. https://doi.org/10.3390/s20071919, 2020.

Carvalho, H.: The air we breathe: Differentials in global air quality monitoring. The Lancet Respiratory Medicine, 4(8), 603–605.

1135   https://doi.org/10.1016/S2213-2600(16)30180-1, 2016.

Casey, J. G., Collier-Oxandale, A., & Hannigan, M.: Performance of artificial neural networks and linear models to quantify 4

trace gas species in an oil and gas production region with low-cost sensors. Sensors and Actuators B: Chemical, 283, 504–

514. https://doi.org/10.1016/j.snb.2018.12.049, 2019.

Castell, N., Dauge, F. R., Schneider, P., Vogt, M., Lerner, U., Fishbain, B., Broday, D., & Bartonova, A.: Can commercial low-

1140   cost sensor platforms contribute to air quality monitoring and exposure estimates? Environment International, 99, 293–302.

https://doi.org/10.1016/j.envint.2016.12.007, 2017.

Castell, N., Schneider, P., Grossberndt, S., Fredriksen, Mirjam. F., Sousa-Santos, G., Vogt, M., & Bartonova, A.: Localized real-

time information on outdoor air quality at kindergartens in Oslo, Norway using low-cost sensor nodes. Environmental

Research, 165, 410–419. https://doi.org/10.1016/j.envres.2017.10.019, 2018.

1145   Chai, T., Kim, H., Pan, L., Lee, P., & Tong, D.: Impact of moderate resolution imaging spectroradiometer aerosol optical depth

and AirNow PM2.5 assimilation on community multi-scale air quality aerosol predictions over the contiguous united

states. Journal of Geophysical Research: Atmospheres, 122(10), 5399–5415. https://doi.org/10.1002/2016JD026295, 2017.

Chang, J. B., Liu, V., Subramanian, V., Sivula, K., Luscombe, C., Murphy, A., Liu, J., & Fréchet, J. M. J.: Printable polythiophene

gas sensor array for low-cost electronic noses. Journal of Applied Physics, 100(1), 014506.

1150   https://doi.org/10.1063/1.2208743, 2006.

Chatzidiakou, L., Archer, R., Beale, V., Bland, S., Carter, H., Castro-Faccetti, C., Edwards, H., Finneran, J., Hama, S., Jones, R.

L., Kumar, P., Linden, P. F., Rawat, N., Roberts, K., Symons, C., Vouriot, C., Wang, D., Way, L., West, S., Weston, D.,

Williams, N., Wood, S., Burridge, H. C.: Schools' air quality monitoring for health and education: Methods and protocols of

the SAMHE initiative and project. Developments in the Built Environment, 16, 100266.

1155   https://doi.org/10.1016/j.dibe.2023.100266, 2023.

Cheadle, L., Deanes, L., Sadighi, K., Gordon Casey, J., Collier-Oxandale, A., & Hannigan, M.: Quantifying neighborhood-scale

spatial variations of ozone at open space and urban sites in Boulder, Colorado using low-cost sensor

technology. Sensors, 17(9), 2072. https://doi.org/10.3390/s17092072, 2017.

Chen, L. C., & Lippmann, M.: Effects of metals within ambient air particulate matter (Pm) on human health. Inhalation

1160   Toxicology, 21(1), 1–31. https://doi.org/10.1080/08958370802105405, 2009.

Chen, W., Yang, Y., Mei, H., Sun, H., Louie, P. K. K., Jiang, S. Y., & Ning, Z.: Analysis of an ozone episode in the Greater Bay

Area based on low-cost sensor network. Atmospheric Environment, 322, 120367.

https://doi.org/10.1016/j.atmosenv.2024.120367, 2024.

Cheng, C., Messerschmidt, L., Bravo, I., Waldbauer, M., Bhavikatti, R., Schenk, C., Grujic, V., Model, T., Kubinec, R., &

1165   Barceló, J.: A general primer for data harmonization. Scientific Data, 11(1), 152. https://doi.org/10.1038/s41597-024-02956-

3, 2024.

Cheng, S., Chang-Chien, G.-P., Huang, Q., Zhang, Y.-B., Yan, P., Zhang, J., Wang, Y., Zhang, D., & Teng, G.: Global research

trends in health effects of volatile organic compounds during the last 16 years: A bibliometric analysis. Aerosol and Air

Quality Research, 19(8), 1834–1843. https://doi.org/10.4209/aaqr.2019.06.0327, 2019.

1170   Clarity Movement Co.: https://www.clarity.io/, last access: 10 March 2024.

Coalition for Clean Air: https://www.ccair.org/, last access: 17 September 2023.

Coker, E. S., Buralli, R., Manrique, A. F., Kanai, C. M., Amegah, A. K., & Gouveia, N.: Association between PM2.5 and

respiratory hospitalization in Rio Branco, Brazil: Demonstrating the potential of low-cost air quality sensor for

epidemiologic research. Environmental Research, 214, 113738. https://doi.org/10.1016/j.envres.2022.113738, 2022.

1175   Collier-Oxandale, A., Casey, J. G., Piedrahita, R., Ortega, J., Halliday, H., Johnston, J., & Hannigan, M. P.: Assessing a low-cost

methane sensor quantification system for use in complex rural and urban environments. Atmospheric Measurement

Techniques, 11(6), 3569–3594. https://doi.org/10.5194/amt-11-3569-2018, 2018.

Collier-Oxandale, A., Coffey, E., Thorson, J., Johnston, J., & Hannigan, M.: Comparing building and neighborhood-scale

variability of co2 and o3 to inform deployment considerations for low-cost sensor system use. Sensors, 18(5), 1349.

1180   https://doi.org/10.3390/s18051349, 2018.

Collier-Oxandale, A., Feenstra, B., Papapostolou, V., Zhang, H., Kuang, M., Der Boghossian, B., & Polidori, A.: Field and

laboratory performance evaluations of 28 gas-phase air quality sensors by the AQ-SPEC program. Atmospheric

Environment, 220, 117092. https://doi.org/10.1016/j.atmosenv.2019.117092, 2020.

Collier-Oxandale, A., Wong, N., Navarro, S., Johnston, J., & Hannigan, M.: Using gas-phase air quality sensors to disentangle

1185   potential sources in a Los Angeles neighborhood. Atmospheric Environment, 233, 117519.

https://doi.org/10.1016/j.atmosenv.2020.117519, 2020.

Connerton, P., Nogueira, T., Kumar, P., & Ribeiro, H.: Use of low-cost sensors for environmental health surveillance: Wildfire-

related particulate matter detection in Brasília, Brazil. Atmosphere, 14(12), 1796. https://doi.org/10.3390/atmos14121796,

2023.

Cross, E. S., Williams, L. R., Lewis, D. K., Magoon, G. R., Onasch, T. B., Kaminsky, M. L., Worsnop, D. R., & Jayne, J. T.: Use

of electrochemical sensors for measurement of air pollution: Correcting interference response and validating

measurements. Atmospheric Measurement Techniques, 10(9), 3575–3588. https://doi.org/10.5194/amt-10-3575-2017, 2017.

David, C. M., River, Q. T., Jorge, R. M., Andres, J. K., & Guillermo, G. L.: A low-cost, rapid-deployment and energy-autonomous

wireless sensor network for air quality monitoring. 2015 9th International Conference on Sensing Technology (ICST), 122–

1195   127. https://doi.org/10.1109/ICSensT.2015.7438376, 2015.

deSouza, P., Nthusi, V., Klopp, J., Shaw, B., Ho, W., Saffell, J., Jones, R., & Ratti, C.: A Nairobi experiment in using low cost air

quality monitors. Clean Air Journal, 27(2). https://doi.org/10.17159/2410-972X/2017/v27n2a6, 2017.

Dewage, P. M. H., Wijeratne, L. O. H., Yu, X., Iqbal, M., Balagopal, G., Waczak, J., Fernando, A., Lary, M. D., Ruwali, S., &

Lary, D. J.: Providing Fine Temporal and Spatial Resolution Analyses of Airborne Particulate Matter Utilizing

1200   Complimentary In Situ IoT Sensor Network and Remote Sensing Approaches. Remote Sensing. 16(13):2454.

https://doi.org/10.3390/rs16132454, 2024.

Dirienzo, N., Mitchell, K., Forde, M., Rainham, D., & Villeneuve, P. J.: Temporal trends in ambient fine particulate matter and the

impacts of COVID-19 on this pollutant in Grenada, West Indies. Journal of the Air & Waste Management

Association, 73(2), 97–108. https://doi.org/10.1080/10962247.2022.2126555, 2023.

Donaldson, K., Mills, N., MacNee, W., Robinson, S., & Newby, D.: Role of inflammation in cardiopulmonary health effects of

PM. Toxicology and Applied Pharmacology, 207(2, Supplement), 483–488. https://doi.org/10.1016/j.taap.2005.02.020,

2005.

Drajic, D. D., & Gligoric, N. R.: Reliable low-cost air quality monitoring using off-the-shelf sensors and statistical calibration. Elektronika Ir Elektrotechnika, 26(2), 32–41. https://doi.org/10.5755/j01.eie.26.2.25734, 2020.

Ekonet: https://ekonet.solutions/air-monitoring, last access: 9 March 2024.

Ellona: https://www.ellona.io/, last access: 10 March 2024.

Ellona customer cases: https://www.ellona.io/customer-case/, last access: 10 March 2024.

E-mote – Envirowatch Ltd.:http://www.envirowatch.ltd.uk/e-mote/, last access: 10 March 2024.

Engel-Cox, J., Kim Oanh, N. T., van Donkelaar, A., Martin, R. V., & Zell, E.: Toward the next generation of air quality monitoring: Particulate Matter. Atmospheric Environment, 80, 584–590. https://doi.org/10.1016/j.atmosenv.2013.08.016, 2013.

Environmental Justice History – U.S. Department of Energy: https://www.energy.gov/lm/environmental-justice-history, last access: 7 March 2024.

EGU General Assembly 2023 Monitoring Networks Session: https://meetingorganizer.copernicus.org/EGU23/session/45206, last access: 18 September 2023.

Fahim, M., El Mhouti, A., Boudaa, T., & Jakimi, A.: Modeling and implementation of a low-cost IoT-smart weather monitoring station and air quality assessment based on fuzzy inference model and MQTT protocol. Modeling Earth Systems and Environment, 9(4), 4085–4102. https://doi.org/10.1007/s40808-023-01701-w, 2023.

Fiedler, N., Laumbach, R., Kelly-McNeil, K., Lioy, P., Fan, Z.-H., Zhang, J., Ottenweller, J., Ohman-Strickland, P., & Kipen, H.: Health effects of a mixture of indoor air volatile organics, their ozone oxidation products, and stress. Environmental Health Perspectives, 113(11), 1542–1548. https://doi.org/10.1289/ehp.8132, 2005.

Fuertes, W., Carrera, D., Villacís, C., Toulkeridis, T., Galárraga, F., Torres, E., & Aules, H.: Distributed system as internet of things for a new low-cost, air pollution wireless monitoring on real time. 2015 IEEE/ACM 19th International Symposium on Distributed Simulation and Real Time Applications (DS-RT), 58–67. https://doi.org/10.1109/DS-RT.2015.28, 2015.

Gagic, R., Skuric, M., Djukanovic, G., Nikolic, D.: Establishing Correlation between Cruise Ship Activities and Ambient PM Concentrations in the Kotor Bay Area Using a Low-Cost Sensor Network. Atmosphere, 13(11), 1819, https://doi.org/10.3390/atmos13111819, 2022.

Giordano, M. R., Malings, C., Pandis, S. N., Presto, A. A., McNeill, V. F., Westervelt, D. M., Beekmann, M., & Subramanian, R.: From low-cost sensors to high-quality data: A summary of challenges and best practices for effectively calibrating low-cost

1235   particulate matter mass sensors. Journal of Aerosol Science, 158, 105833. https://doi.org/10.1016/j.jaerosci.2021.105833, 2021.

Gnamien, S., Yoboué, V., Liousse, C., Ossohou, M., Keita, S., Bahino, J., Siélé, S., & Diaby, L.: Particulate pollution in korhogo and abidjan (Cote d'Ivoire) during the dry season. Aerosol and Air Quality Research, 21(1), 200201. https://doi.org/10.4209/aaqr.2020.05.0201, 2021.

1240 González Rivero, R. A., Schalm, O., Alvarez Cruz, A., Hernández Rodríguez, E., Morales Pérez, M. C., Alejo Sánchez, D., Martinez Laguardia, A., Jacobs, W., & Hernández Santana, L.: Relevance and reliability of outdoor so2 monitoring in low-income countries using low-cost sensors. Atmosphere, 14(6), 912. https://doi.org/10.3390/atmos14060912, 2023.

Gramsch, E., Morales, L., Baeza, M., Ayala, C., Soto, C., Neira, J., Pérez, P., & Moreno, F.: Citizens' surveillance micro-network for the mapping of pm2. 5 in the city of Concón, Chile. Aerosol and Air Quality Research, 20(2), 358–368.

1245   https://doi.org/10.4209/aaqr.2019.04.0179, 2020.

Gramsch, E., Oyola, P., Reyes, F., Vásquez, Y., Rubio, M. A., Soto, C., Pérez, P., Moreno, F., & Gutiérrez, N.: Influence of particle composition and size on the accuracy of low cost pm sensors: Findings from field campaigns. Frontiers in Environmental Science, 9. https://doi.org/10.3389/fenvs.2021.751267, 2021.

Granados-Bolaños, S., Quesada-Román, A., & Alvarado, G. E.: Low-cost applications in dynamic tropical volcanic

1250   landforms. Journal of Volcanology and Geothermal Research, 410, 107143. https://doi.org/10.1016/j.jvolgeores.2020.107143, 2021.

Gressent, A., Malherbe, L., Colette, A., Rollin, H., & Scimia, R.: Data fusion for air quality mapping using low-cost sensor observations: Feasibility and added-value. Environment International, 143, 105965. https://doi.org/10.1016/j.envint.2020.105965, 2020.

1255 Gryech, I., Ben-Aboud, Y., Guermah, B., Sbihi, N., Ghogho, M., & Kobbane, A.: Moreair: A low-cost urban air pollution monitoring system. Sensors, 20(4), 998. https://doi.org/10.3390/s20040998, 2020.

Guanochanga, B., Cachipuendo, R., Fuertes, W., Benítez, D. S., Toulkeridis, T., Torres, J., Villacís, C., Tapia, F., & Meneses, F.: Towards a real-time air pollution monitoring systems implemented using wireless sensor networks: Preliminary results. 2018 IEEE Colombian Conference on Communications and Computing (COLCOM), 1–4.

1260 https://doi.org/10.1109/ColComCon.2018.8466721, 2018.

Guevara, J., Vargas, E., Barrero, F., & Toral, S.: Ubiquitous architecture for environmental sensor networks in road traffic applications. 13th International IEEE Conference on Intelligent Transportation Systems, 1227–1232. https://doi.org/10.1109/ITSC.2010.5625110, 2010

Hagan, D. H., Gani, S., Bhandari, S., Patel, K., Habib, G., Apte, J. S., Hildebrandt Ruiz, L., & Kroll, J. H.: Inferring aerosol

1265 sources from low-cost air quality sensor measurements: A case study in Delhi, India. Environmental Science & Technology Letters, 6(8), 467–472. https://doi.org/10.1021/acs.estlett.9b00393, 2019.

Han, P., Mei, H., Liu, D., Zeng, N., Tang, X., Wang, Y., & Pan, Y.: Calibrations of low-cost air pollution monitoring sensors for co, no2, o3, and so2. Sensors, 21(1), 256. https://doi.org/10.3390/s21010256, 2021.

Hemingway, S. E.: 2022 Air Sensors International Conference Program Topics. https://asic.aqrc.ucdavis.edu/2022-program-topics,

1270 2022.

Hodoli, C. G., Coulon, F., & Mead, M. I.: Source identification with high-temporal resolution data from low-cost sensors using bivariate polar plots in urban areas of Ghana. Environmental Pollution, 317, 120448. https://doi.org/10.1016/j.envpol.2022.120448, 2023.

Hodoli, C. G., & the Network for Atmospheric and Air Quality Research (NAAQR): Sensors as a component of urban air quality

1275 management planning: a case study with AirGradient OpenAir PM monitors from Accra, Ghana. EGU General Assembly 2024, EGU24-20857. https://doi.org/10.5194/egusphere-egu24-20857, 2024.

Hofman, J., Peters, J., Stroobants, C., Elst, E., Baeyens, B., Van Laer, J., Spruyt, M., Van Essche, W., Delbare, E., Roels, B., Cochez, A., Gillijns, E., & Van Poppel, M.: Air quality sensor networks for evidence-based policy making: Best practices for actionable insights. Atmosphere, 13(6), 944. https://doi.org/10.3390/atmos13060944, 2022.

Iao, J., Wang, F., & Shen, H.: The influence of PM2.5 exposure duration and concentration on outpatient visits of urban hospital in a typical heavy industrial city. Environmental Science and Pollution Research, 30(54), 115098–115110. https://doi.org/10.1007/s11356-023-30544-2, 2023.

Ibarrola, E.: Considerations when deploying a sensor-based air quality network. Air Sensors International Conference. https://asic.aqrc.ucdavis.edu/sites/g/files/dgvnsk3466/files/inline-files/Edurne%20Ibarolla%20-%20Considerations%20when%20deploying%20a%20sensor-based%20air%20quality%20network%20.pdf, 2022.

IQAir AirVisual Platform: https://www.iqair.com/us/commercial-air-quality-monitors/airvisual-platform, last access: 9 March 2024.

IQAir: First in air quality: https://www.iqair.com/, last access: 17 September 2023.

IQAir live animated air quality map: https://www.iqair.com/us/air-quality-map, last access: 9 March 2024.

Is there an Introductory guide on how to utilize the API to analyze historical data? PurpleAir Community. https://community.purpleair.com/t/is-there-an-introductory-guide-on-how-to-utilise-the-api-to-analyse-historical-data/3148/3, last access: 10 March 2024.

Jain, S., Presto, A. A., & Zimmerman, N.: Spatial modeling of daily PM2.5, NO, and CO concentrations measured by a low-cost sensor network: Comparison of linear, machine learning, and hybrid land use models. Environmental Science & Technology, 55(13), 8631–8641. https://doi.org/10.1021/acs.est.1c02653, 2021.

Jang, Y.-W., & Jung, G.-W.: Temporal characteristics and sources of PM2.5 in Porto Velho of Amazon region in Brazil from 2020 to 2022. Sustainability, 15(18), 14012. https://doi.org/10.3390/su151814012, 2023.

Jayaratne, R., Kuhn, T., Christensen, B., Liu, X., Zing, I., Lamont, R., Dunbabin, M., Maddox, J., Fisher, G., Morawska, L.: Using a network of low-cost particle sensors to assess the impact of ship emissions on a residential community. Aerosol and Air Quality Research, 20(12), 2754. 10.4209/aaqr.2020.06.0280, 2020.

Jayaratne, R., Liu, X., Thai, P., Dunbabin, M., & Morawska, L.: The influence of humidity on the performance of a low-cost air particle mass sensor and the effect of atmospheric fog. Atmospheric Measurement Techniques, 11(8), 4883–4890. https://doi.org/10.5194/amt-11-4883-2018, 2018.

Jayaratne, R., Thai, P., Christensen, B., Liu, X., Zing, I., Lamont, R., Dunbabin, M., Dawkins, L., Bertrand, L., & Morawska, L.:

1305   The effect of cold-start emissions on the diurnal variation of carbon monoxide concentration in a city centre. Atmospheric

Environment, 245, 118035. https://doi.org/10.1016/j.atmosenv.2020.118035, 2021.

Jeong, J. I., & Park, R. J.: Effects of the meteorological variability on regional air quality in East Asia. Atmospheric

Environment, 69, 46–55. https://doi.org/10.1016/j.atmosenv.2012.11.061, 2013.

Jiao, W., Hagler, G. S. W., Williams, R. W., Sharpe, R. N., Weinstock, L., & Rice, J.: Field assessment of the village green

1310   project: An autonomous community air quality monitoring system. Environmental Science & Technology, 49(10), 6085–

6092. https://doi.org/10.1021/acs.est.5b01245, 2015.

Jiao, W., Hagler, G., Williams, R., Sharpe, R., Brown, R., Garver, D., Judge, R., Caudill, M., Rickard, J., Davis, M., Weinstock,

L., Zimmer-Dauphinee, S., & Buckley, K.: Community Air Sensor Network (Cairsense) project: Evaluation of low-cost

sensor performance in a suburban environment in the southeastern United States. Atmospheric Measurement

1315   Techniques, 9(11), 5281–5292. https://doi.org/10.5194/amt-9-5281-2016, 2016.

Jing, P., Schusler, T., Dahal, D., Zhang, B., Fischer, E., Pollack, I. B., & Sablan, O. M.: Community air research experience

(Care): Engaging undergraduate students underrepresented in stem fields in research on air pollution in chicago

communities. ED42C-0608. https://ui.adsabs.harvard.edu/abs/2022AGUFMED42C0608J, 2022.

Johnston, J. E., Enebish, T., Eckel, S. P., Navarro, S., & Shamasunder, B.: Respiratory health, pulmonary function and local

1320   engagement in urban communities near oil development. Environmental Research, 197, 111088.

https://doi.org/10.1016/j.envres.2021.111088, 2021.

Jovašević-Stojanović, M., Bartonova, A., Topalović, D., Lazović, I., Pokrić, B., & Ristovski, Z.: On the use of small and cheaper

sensors and devices for indicative citizen-based monitoring of respirable particulate matter. Environmental Pollution, 206,

696–704. https://doi.org/10.1016/j.envpol.2015.08.035, 2015.

1325   Kampa, M., & Castanas, E.: Human health effects of air pollution. Environmental Pollution, 151(2), 362–367.

https://doi.org/10.1016/j.envpol.2007.06.012, 2008.

Karagulian, F., Barbiere, M., Kotsev, A., Spinelle, L., Gerboles, M., Lagler, F., Redon, N., Crunaire, S., & Borowiak, A. Review of the performance of low-cost sensors for air quality monitoring. Atmosphere, 10(9), 506. https://doi.org/10.3390/atmos10090506, 2019.

Karaoghlanian, N., Noureddine, B., Saliba, N., Shihadeh, A., & Lakkis, I.: Low cost air quality sensors "PurpleAir" calibration and inter-calibration dataset in the context of Beirut, Lebanon. Data in Brief, 41, 108008. https://doi.org/10.1016/j.dib.2022.108008, 2022.

Kelly, K. E., Whitaker, J., Petty, A., Widmer, C., Dybwad, A., Sleeth, D., Martin, R., & Butterfield, A.: Ambient and laboratory evaluation of a low-cost particulate matter sensor. Environmental Pollution, 221, 491–500. https://doi.org/10.1016/j.envpol.2016.12.039, 2017.

Khader, A., & Martin, R. S.: Use of low-cost ambient particulate sensors in Nablus, Palestine with application to the assessment of regional dust storms. Atmosphere, 10(9), 539. https://doi.org/10.3390/atmos10090539, 2019.

Khan, T. R., & Meranger, J. C.: Recent advances in SO2, NOx, and O3 personal monitoring. Environment International, 9(3), 195–206. https://doi.org/10.1016/0160-4120(83)90037-5, 1983.

Khuriganova, O. I., Obolkin, V. A., Golobokova, L. P., Bukin, Y. S., & Khodzher, T. V.: Passive sampling as a low-cost method for monitoring air pollutants in the Baikal region (Eastern Siberia). Atmosphere, 10(8), 470. https://doi.org/10.3390/atmos10080470, 2019.

Kim, J., Shusterman, A. A., Lieschke, K. J., Newman, C., & Cohen, R. C.: The BErkeley Atmospheric CO_2 Observation Network: Field calibration and evaluation of low-cost air quality sensors. Atmospheric Measurement Techniques, 11(4), 1937–1946. https://doi.org/10.5194/amt-11-1937-2018, 2018.

Korotchenkov, G. S., Dmitriev, S. V., & Brynzari, V. I.: Processes development for low cost and low power consuming SnO2 thin film gas sensors (Tfgs). Sensors and Actuators B: Chemical, 54(3), 202–209. https://doi.org/10.1016/S0925-4005(99)00017-9, 1999.

Kotzagianni, M., Hassani, A., Morresi, N., Udina, S., Kyfonidis, C., Roussos, A., Casaccia, S., Revel, G. M., & Noriega-Ortega, B.: Calibration strategies for low-cost compact field sensors in Citizen Science Air Quality measurements: Insights from

SOCIO-BEE project. 2023 8th International Conference on Smart and Sustainable Technologies (SpliTech), 1–6. https://doi.org/10.23919/SpliTech58164.2023.10193423, 2023.

Kuhn, T., Jayaratne, R., Thai, P. K., Christensen, B., Liu, X., Dunbabin, M., Lamont, R., Zing, I., Wainwright, D., Witte, C., Neale, D., & Morawska, L.: Air quality during and after the Commonwealth Games 2018 in Australia: Multiple benefits of monitoring. Journal of Aerosol Science, 152, 105707. https://doi.org/10.1016/j.jaerosci.2020.105707, 2021.

Kumar, T., & Doss, A.: Airo: Development of an intelligent IOT-based air quality monitoring solution for urban areas. Procedia Computer Science, 218, 262–273. https://doi.org/10.1016/j.procs.2023.01.008, 2023.

Kurtenbach, R., Ulianova, K., Gibilisco, R. G., Villena, G., & Wiesen, P.: Validation of low cost sensors for gases and particulate matter in the city centre of Wuppertal, Germany. Proceedings of the 24th International Transport and Air Pollution (TAP) Conference. https://data.europa.eu/doi/10.2760/019404, 2022.

Labzovskii, L. D., Vande Hey, J., Romanov, A. A., Golovatina-Mora, P., Belikov, D. A., Lashkari, A., Takele Kenea, S., & Hekman, E.: Who should measure air quality in modern cities? The example of decentralization of urban air quality monitoring in Krasnoyarsk (Siberia, Russia). Environmental Science & Policy, 140, 93-103. https://doi.org/10.1016/j.envsci.2022.11.016, 2023.

Lassman, W., Pierce, J. R., Bangs, E. J., Sullivan, A. P., Ford, B., Mengistu Tsidu, G., Sherman, J. P., Collett, J. L., & Bililign, S.: Using low-cost measurement systems to investigate air quality: A case study in Palapye, Botswana. Atmosphere, 11(6), 583. https://doi.org/10.3390/atmos11060583, 2020.

Lee, Y.-M., Lin, G.-Y., Le, T.-C., Hong, G.-H., Aggarwal, S. G., Yu, J.-Y., & Tsai, C.-J.: Characterization of spatial-temporal distribution and microenvironment source contribution of PM2.5 concentrations using a low-cost sensor network with artificial neural network/kriging techniques. Environmental Research, 244, 117906. https://doi.org/10.1016/j.envres.2023.117906, 2024.

Li, H. Z., Gu, P., Ye, Q., Zimmerman, N., Robinson, E. S., Subramanian, R., Apte, J. S., Robinson, A. L., & Presto, A. A.: Spatially dense air pollutant sampling: Implications of spatial variability on the representativeness of stationary air pollutant monitors. Atmospheric Environment: X, 2, 100012. https://doi.org/10.1016/j.aeaoa.2019.100012, 2019.

Li, J., Zhang, H., Chao, C.-Y., Chien, C.-H., Wu, C.-Y., Luo, C. H., Chen, L.-J., & Biswas, P.: Integrating low-cost air quality

1375   sensor networks with fixed and satellite monitoring systems to study ground-level PM2.5. Atmospheric Environment, 223,

117293. https://doi.org/10.1016/j.atmosenv.2020.117293, 2020.

Liang, L., Daniels, J., Bailey, C., Hu, L., Phillips, R., & South, J.: Integrating low-cost sensor monitoring, satellite mapping, and

geospatial artificial intelligence for intra-urban air pollution predictions. Environmental Pollution, 331, 121832.

https://doi.org/10.1016/j.envpol.2023.121832, 2023.

1380 Liu, C., Labzovskii, L. D., Leung Mak, H. W., Fung, J. C. H., Lau, A. K. H., Kenea, S. T., Bilal, M., Vande Hey, J. D., Lu, X., &

Ma, J.: Observation of PM2.5 using a combination of satellite remote sensing and low-cost sensor network in Siberian urban

areas with limited reference monitoring. Atmospheric Environment, 227, 117410.

https://doi.org/10.1016/j.atmosenv.2020.117410, 2020.

Liu, J., Banerjee, S., Oroumiyeh, F., Shen, J., del Rosario, I., Lipsitt, J., Paulson, S., Ritz, B., Su, J., Weichenthal, S., Lakey, P.,

1385   Shiraiwa, M., Zhu, Y., & Jerrett, M.: Co-kriging with a low-cost sensor network to estimate spatial variation of brake and

tire-wear metals and oxidative stress potential in Southern California. Environment International, 168, 107481.

https://doi.org/10.1016/j.envint.2022.107481, 2022.

Liu, M., K. Barkjohn, K., Norris, C., J. Schauer, J., Zhang, J., Zhang, Y., Hu, M., & Bergin, M.: Using low-cost sensors to monitor

indoor, outdoor, and personal ozone concentrations in Beijing, China. Environmental Science: Processes & Impacts, 22(1),

1390   131–143. https://doi.org/10.1039/C9EM00377K, 2020.

Liu, N., Bu, Z., Liu, W., Kan, H., Zhao, Z., Deng, F., Huang, C., Zhao, B., Zeng, X., Sun, Y., Qian, H., Mo, J., Sun, C., Guo, J.,

Zheng, X., Weschler, L. B., & Zhang, Y.: Health effects of exposure to indoor volatile organic compounds from 1980 to

2017: A systematic review and meta-analysis. Indoor Air, 32(5). https://doi.org/10.1111/ina.13038, 2022.

Liu, S., Yang, X., & Zhou, X.: Development of a low-cost UAV-based system for CH4 monitoring over oil fields. Environmental

1395   Technology, 42(20), 3154–3163. https://doi.org/10.1080/09593330.2020.1724199, 2020.

Liu, X., Jayaratne, R., Thai, P., Kuhn, T., Zing, I., Christensen, B., Lamont, R., Dunbabin, M., Zhu, S., Gao, J., Wainwright, D.,

Neale, D., Kan, R., Kirkwood, J., & Morawska, L.: Low-cost sensors as an alternative for long-term air quality

monitoring. Environmental Research, 185, 109438. https://doi.org/10.1016/j.envres.2020.109438, 2020.

Local Haze [Mobile App]: https://localhaze.humanlogic.com/, last access: 17 September 2023.

1400 Lopez-Restrepo, S., Yarce, A., Pinel, N., Quintero, O. L., Segers, A., & Heemink, A. W.: Urban air quality modeling using low-cost sensor network and data assimilation in the Aburrá Valley, Colombia. Atmosphere, 12(1), 91. https://doi.org/10.3390/atmos12010091, 2021.

Love my air: https://denver.lovemyair.com, last access: 10 March 2024.

Love my air Wisconsin - Children's Health Alliance of Wisconsin: https://www.chawisconsin.org/initiatives/environmental-

1405   health/air-quality/, last access: 10 March 2024.

Lu, T., Liu, Y., Garcia, A., Wang, M., Li, Y., Bravo-Villasenor, G., Campos, K., Xu, J., & Han, B.: Leveraging citizen science and low-cost sensors to characterize air pollution exposure of disadvantaged communities in southern california. International Journal of Environmental Research and Public Health, 19(14), 8777. https://doi.org/10.3390/ijerph19148777, 2022.

Ma, Y., Richards, M., Ghanem, M., Guo, Y., & Hassard, J.: Air pollution monitoring and mining based on sensor grid in

1410   london. Sensors, 8(6), 3601–3623. https://doi.org/10.3390/s80603601, 2008.

Mahfuz, M. U., & Ahmed, K.: A review of micro-nano-scale wireless sensor networks for environmental protection: Prospects and challenges. Science and Technology of Advanced Materials, 6(3–4), 302–306. https://doi.org/10.1016/j.stam.2005.02.008, 2005.

Malings, C., Knowland, K. E., Keller, C. A., & Cohn, S. E.: Sub-city scale hourly air quality forecasting by combining models,

1415   satellite observations, and ground measurements. Earth and Space Science, 8(7), e2021EA001743. https://doi.org/10.1029/2021EA001743, 2021.

Malings, C., Tanzer, R., Hauryliuk, A., Kumar, S. P. N., Zimmerman, N., Kara, L. B., Presto, A. A., & R. Subramanian. Development of a general calibration model and long-term performance evaluation of low-cost sensors for air pollutant gas monitoring. Atmospheric Measurement Techniques, 12(2), 903–920. https://doi.org/10.5194/amt-12-903-2019, 2019.

1420 Malings, C., Tanzer, R., Hauryliuk, A., Saha, P. K., Robinson, A. L., Presto, A. A., & Subramanian, R.: Fine particle mass monitoring with low-cost sensors: Corrections and long-term performance evaluation. Aerosol Science and Technology, 54(2), 160–174. https://doi.org/10.1080/02786826.2019.1623863, 2019.

Map of smartcitizen kits: https://smartcitizen.me/kits, last access: 10 March 2024.

Martinez, A., Hernandez-Rodríguez, E., Hernandez, L., Schalm, O., González-Rivero, R. A., & Alejo-Sánchez, D.: Design of a

1425   low-cost system for the measurement of variables associated with air quality. IEEE Embedded Systems Letters, 15(2), 105–

108. https://doi.org/10.1109/LES.2022.3196543, 2023.

Mead, M. I., Popoola, O. A. M., Stewart, G. B., Landshoff, P., Calleja, M., Hayes, M., Baldovi, J. J., McLeod, M. W., Hodgson, T.

F., Dicks, J., Lewis, A., Cohen, J., Baron, R., Saffell, J. R., & Jones, R. L.: The use of electrochemical sensors for

monitoring urban air quality in low-cost, high-density networks. Atmospheric Environment, 70, 186–203.

1430   https://doi.org/10.1016/j.atmosenv.2012.11.060, 2013.

Meixner, H., Gerblinger, J., Lampe, U., & Fleischer, M.: Thin-film gas sensors based on semiconducting metal oxides. Sensors

and Actuators B: Chemical, 23(2–3), 119–125. https://doi.org/10.1016/0925-4005(94)01266-K, 1995.

Meixner, H., & Lampe, U.: Metal oxide sensors. Sensors and Actuators B: Chemical, 33(1–3), 198–202.

https://doi.org/10.1016/0925-4005(96)80098-0, 1996.

1435   Metreveli, Y.Y.: IOP Conf. Ser.: Earth Environ. Sci., 872, 012015. 10.1088/1755-1315/872/1/012015, 2021.

Miranda, M. L., Edwards, S. E., Keating, M. H., & Paul, C. J.: Making the environmental justice grade: The relative burden of air

pollution exposure in the united states. International Journal of Environmental Research and Public Health, 8(6), 1755–1771.

https://doi.org/10.3390/ijerph8061755, 2011.

Miskell, G., Salmond, J., & Williams, D. E.: Low-cost sensors and crowd-sourced data: Observations of siting impacts on a

1440   network of air-quality instruments. Science of The Total Environment, 575, 1119–1129.

https://doi.org/10.1016/j.scitotenv.2016.09.177, 2017.

MKE FreshAir Collective: https://www.mkefreshair.com/, last access: 10 March 2024.

Mo, X., Peters, D., Lei, C.: Low Cost Autonomous UAV Swarm Application in Wildfire Surveillance and Suppression.

Proceedings of the 2021 6th International Conference on Machine Learning Technologies, 164–169.

1445   https://doi.org/10.1145/3468891.3468916, 2021.

Moltchanov, S., Levy, I., Etzion, Y., Lerner, U., Broday, D. M., & Fishbain, B.: On the feasibility of measuring urban air pollution

by wireless distributed sensor networks. Science of The Total Environment, 502, 537–547.

https://doi.org/10.1016/j.scitotenv.2014.09.059, 2015.

Morawska, L., Thai, P. K., Liu, X., Asumadu-Sakyi, A., Ayoko, G., Bartonova, A., Bedini, A., Chai, F., Christensen, B., Dunbabin, M., Gao, J., Hagler, G. S. W., Jayaratne, R., Kumar, P., Lau, A. K. H., Louie, P. K. K., Mazaheri, M., Ning, Z., Motta, N., … Williams, R.: Applications of low-cost sensing technologies for air quality monitoring and exposure assessment: How far have they gone? Environment International, 116, 286–299. https://doi.org/10.1016/j.envint.2018.04.018, 2018.

Morel, P.: Gramm: Grammar of graphics plotting in Matlab. The Journal of Open Source Software, 3(23), 568. https://doi.org/10.21105/joss.00568, 2018.

Morgan, M. G., & Morris, S. C.: Individual air pollution monitors: An assessment of national research needs(BNL-50482, 7293144; p. BNL-50482, 7293144). https://doi.org/10.2172/7293144, 1976.

Mullen, C. J., Grineski, S. E., Collins, T. W., & Flores, A. B.: Air quality sensors and distributional environmental justice: A case study of Salt Lake County, Utah. Environmental Sociology, 1–13. https://doi.org/10.1080/23251042.2023.2295099, 2023.

Müller, M., Graf, P., Meyer, J., Pentina, A., Brunner, D., Perez-Cruz, F., Hüglin, C., & Emmenegger, L.: Integration and calibration of non-dispersive infrared (Ndir) CO_2 low-cost sensors and their operation in a sensor network covering Switzerland. Atmospheric Measurement Techniques, 13(7), 3815–3834. https://doi.org/10.5194/amt-13-3815-2020, 2020.

Munir, S., Mayfield, M., Coca, D., Jubb, S. A., & Osammor, O.: Analysing the performance of low-cost air quality sensors, their drivers, relative benefits and calibration in cities—A case study in Sheffield. Environmental Monitoring and Assessment, 191(2), 94. https://doi.org/10.1007/s10661-019-7231-8, 2019.

Narayana, M. V., Jalihal, D., & Nagendra, S. M. S.: Establishing a sustainable low-cost air quality monitoring setup: A survey of the state-of-the-art. Sensors, 22(1), 394. https://doi.org/10.3390/s22010394, 2022.

NASA Ames INSTEP: https://www.nasa.gov/inexpensive-network-sensor-technology-exploring-pollution-instep/, last access: 10 March 2024.

National Ambient Air Quality Standards - California Air Resources Board: https://ww2.arb.ca.gov/resources/national-ambient-air-quality-standards, last access: 17 September 2023.

National Research Council (US) Committee on Indoor Pollutants: Monitoring and modeling of indoor air pollution. In Indoor Pollutants. National Academies Press (US). https://www.ncbi.nlm.nih.gov/books/NBK234059/, 1981.

Pereira-Rodrigues, N., Guillot, J.M., Fanlo, J.L, Renner, C., & Aubert, B.: Miniature and low-cost devices for the precise and

1475   reliable monitoring of low concentrations of h2s in changing environments. Chemical Engineering Transactions, 23, 237–

242. https://doi.org/10.3303/CET1023040, 2010.

National Association of Clean Air Agencies: https://www.4cleanair.org/, last access: 17 September 2023.

Ndamuzi, E., Akimana, R., Gahungu, P., & Bimenyimana, E.: Modelling and characterization of fine Particulate Matter dynamics

in Bujumbura using low cost sensors. arXiv.Org. https://arxiv.org/abs/2312.12003v1, 2023.

1480Ngo, N. S., Asseko, S. V. J., Ebanega, M. O., Allo'o Allo'o, S. M., & Hystad, P.: The relationship among PM2.5, traffic

emissions, and socioeconomic status: Evidence from Gabon using low-cost, portable air quality monitors. Transportation

Research Part D: Transport and Environment, 68, 2–9. https://doi.org/10.1016/j.trd.2018.01.029, 2019.

Ngom, B., Seye, M. R., Diallo, M., Gueye, B., & Drame, M. S.: A hybrid measurement kit for real-time air quality monitoring

across senegal cities. 2018 1st International Conference on Smart Cities and Communities (SCCIC), 1–6.

1485   https://doi.org/10.1109/SCCIC.2018.8584551, 2018.

Nori-Sarma, A., Thimmulappa, R. K., Venkataramana, G. V., Fauzie, A. K., Dey, S. K., Venkareddy, L. K., Berman, J. D., Lane,

K. J., Fong, K. C., Warren, J. L., & Bell, M. L.: Low-cost NO2 monitoring and predictions of urban exposure using universal

kriging and land-use regression modelling in Mysore, India. Atmospheric Environment, 226, 117395.

https://doi.org/10.1016/j.atmosenv.2020.117395, 2020.

1490Oizom: https://oizom.com/, last access: 10 March 2024.

Okorn, K., & Hannigan, M.: Applications and limitations of quantifying speciated and source-apportioned vocs with metal oxide

sensors. Atmosphere, 12(11), 1383. https://doi.org/10.3390/atmos12111383, 2021.

Okorn, K., Jimenez, A., Collier-Oxandale, A., Johnston, J., & Hannigan, M.: Characterizing methane and total non-methane

hydrocarbon levels in Los Angeles communities with oil and gas facilities using air quality monitors. Science of The Total

1495   Environment, 777, 146194. https://doi.org/10.1016/j.scitotenv.2021.146194, 2021.

Omokungbe, O. R., Fawole, O. G., Owoade, O. K., Popoola, O. A. M., Jones, R. L., Olise, F. S., Ayoola, M. A., Abiodun, P. O.,

Toyeje, A. B., Olufemi, A. P., Sunmonu, L. A., & Abiye, O. E.: Analysis of the variability of airborne particulate matter with

prevailing meteorological conditions across a semi-urban environment using a network of low-cost air quality

sensors. Heliyon, 6(6), e04207. https://doi.org/10.1016/j.heliyon.2020.e04207, 2020.

1500 Omokungbe, O. R., Olufemi, A. P., Toyeje, A. B., & Abiodun, P. O.: Investigating the evolution of gaseous air pollutants with

prevailing meteorology across selected sites within a pollution hotspot in Ile-Ife, Southwestern Nigeria. Discover

Environment, 1(1), 5. https://doi.org/10.1007/s44274-023-00006-0, 2023.

Open map - Clarity movement: https://openmap.clarity.io/, last access: 9 March 2024.

OpenAQ: https://openaq.org/, last access: 10 March 2024.

1505 Ott, W. R.: Concepts of human exposure to air pollution. Environment International, 7(3), 179–196. https://doi.org/10.1016/0160-

4120(82)90104-0, 1982.

Outpost environmental: https://outpostenvironmental.com/, last access: 10 March 2024.

Ouyang, B., Popoola, L., Jones, R., Li, C., & Chen, J.: Portable and low-cost sensors in monitoring air qualities in China.

EPSC2016-16213. https://ui.adsabs.harvard.edu/abs/2016EGUGA..1816213O, 2016.

1510 Owoade, O. K., Abiodun, P. O., Omokungbe, O. R., Fawole, O. G., Olise, F. S., Popoola, O. O. M., Jones, R. L., & Hopke, P. K.:

Spatial-temporal variation and local source identification of air pollutants in a semi-urban settlement in Nigeria using low-

cost sensors. Aerosol and Air Quality Research, 21(10), 200598. https://doi.org/10.4209/aaqr.200598, 2021.

Oyola, P., Carbone, S., Timonen, H., Torkmahalleh, M., & Lindén, J.: Editorial: Rise of low-cost sensors and citizen science in air

quality studies. Frontiers in Environmental Science, 10, 868543. https://doi.org/10.3389/fenvs.2022.868543, 2022.

1515 Ozler, S.: Field applications of low-cost air quality monitors for pm 2. 5 studies [Thesis].

https://minds.wisconsin.edu/handle/1793/78604, 2018.

Paku for PurpleAir: https://paku.app, last access: 9 March 2024.

Panzitta Alessandra, Bax Carmen, Lotesoriere Beatrice J., Ratti Christian, & Capelli Laura: Realisation of a multi-sensor system

for real-time monitoring of odour emissions at a waste treatment plant. Chemical Engineering Transactions, 95, 139–144.

1520 https://doi.org/10.3303/CET2295024, 2022.

Papaconstantinou, R., Demosthenous, M., Bezantakos, S., Hadjigeorgiou, N., Costi, M., Stylianou, M., Symeou, E., Savvides, C.,

& Biskos, G.: Field evaluation of low-cost electrochemical air quality gas sensors under extreme temperature and relative

humidity conditions. Atmospheric Measurement Techniques, 16(12), 3313–3329. https://doi.org/10.5194/amt-16-3313-2023, 2023.

1525 Papadopoulos, C. A., Vlachos, D. S., & Avaritsiotis, J. N.: Comparative study of various metal-oxide-based gas-sensor architectures. Sensors and Actuators B: Chemical, 32(1), 61–69. https://doi.org/10.1016/0925-4005(96)80110-9, 1996.

Park, C., Jeong, S., Park, H., Woo, J.-H., Sim, S., Kim, J., Son, J., Park, H., Shin, Y., Shin, J., Kwon, S.-M., & Lee, W.: Challenges in monitoring atmospheric co2 concentrations in Seoul using low-cost sensors. Asia-Pacific Journal of Atmospheric Sciences, 57(3), 547–553. https://doi.org/10.1007/s13143-020-00213-2, 2021.

1530 Past Meetings - NASA HAQAST (NASA Health and Air Quality Applied Sciences Team): https://haqast.org/get-involved/meetings/, last access: 17 September 2023.

Patwardhan, I., Sara, S., & Chaudhari, S.: Comparative evaluation of new low-cost particulate matter sensors. 2021 8th International Conference on Future Internet of Things and Cloud (FiCloud), 192–197. https://doi.org/10.1109/FiCloud49777.2021.00035, 2021.

1535 Penza, M., Suriano, D., Cassano, G., Pfister, V., Amodio, M., Trizio, L., Brattoli, M., & De Gennaro, G.: A case-study of microsensors for landfill air-pollution monitoring applications. Urban Climate, 14, 351–369. https://doi.org/10.1016/j.uclim.2014.09.002, 2015.

Penza, M., Suriano, D., Pfister, V., Prato, M., & Cassano, G.: Urban air quality monitoring with networked low-cost sensor-systems. Proceedings, 1(4), 573. https://doi.org/10.3390/proceedings1040573, 2017.

1540 Penza, M., Suriano, D., Villani, M. G., Spinelle, L., & Gerboles, M.: Towards air quality indices in smart cities by calibrated low-cost sensors applied to networks. 2014 IEEE SENSORS, 2012–2017. https://doi.org/10.1109/ICSENS.2014.6985429, 2014.

Perello, J.: Bettair. https://www.miteco.gob.es/content/dam/miteco/es/calidad-y-evaluacion-ambiental/formacion/ateknea_bettair_jornada_sensores_20180605_tcm30-457716.pdf, 2018.

Piedrahita, R., Xiang, Y., Masson, N., Ortega, J., Collier, A., Jiang, Y., Li, K., Dick, R. P., Lv, Q., Hannigan, M., & Shang, L.: The
1545 next generation of low-cost personal air quality sensors for quantitative exposure monitoring. Atmospheric Measurement Techniques, 7(10), 3325–3336. https://doi.org/10.5194/amt-7-3325-2014, 2014.

Pochwala, S., Gardecki, A., Lewandowski, P., Somogyi, V., Anweiler, S.: Developing of Low-Cost Air Pollution Sensor— Measurements with the Unmanned Aerial Vehicles in Poland. Sensors, 20, 3582. https://doi.org/10.3390/s20123582, 2020.

Pope, C. A., & Dockery, D. W.: Health effects of fine particulate air pollution: Lines that connect. Journal of the Air & Waste Management Association, 56(6), 709–742. https://doi.org/10.1080/10473289.2006.10464485, 2006.

Pope, F. D., Gatari, M., Ng'ang'a, D., Poynter, A., & Blake, R.: Airborne particulate matter monitoring in Kenya using calibrated low-cost sensors. Atmospheric Chemistry and Physics, 18(20), 15403–15418. https://doi.org/10.5194/acp-18-15403-2018, 2018.

Popoola, O. A. M., Carruthers, D., Lad, C., Bright, V. B., Mead, M. I., Stettler, M. E. J., Saffell, J. R., & Jones, R. L.: Use of networks of low cost air quality sensors to quantify air quality in urban settings. Atmospheric Environment, 194, 58–70. https://doi.org/10.1016/j.atmosenv.2018.09.030, 2018l

Postolache, O. A., Pereira, J. M. D., & Girao, P. M. B. S.: Smart sensors network for air quality monitoring applications. IEEE Transactions on Instrumentation and Measurement, 58(9), 3253–3262. https://doi.org/10.1109/TIM.2009.2022372, 2009.

Prana Air: https:/pranaair.com, last access: 9 March 2024.

Prathibha, P. S., Cross, E. S., Strehl, R. L., Yeager, R. A., II, Bhatnagar, A., & Turner, J. R.: Green heart louisville: Community-level assessment of exposure to air pollution. 2020, A206-02. https://ui.adsabs.harvard.edu/abs/2020AGUFMA206...02P, 2020.

Projects Archive - Thriving Earth Exchange: https://thrivingearthexchange.org/projects/, last access: 17 September 2017.

PurpleAir real-time air quality map: from https://map.purpleair.com/, last access: 9 March 2024.

PurpleAir's new API dashboard & data download tool release: https://www2.purpleair.com/blogs/blog-home/purpleair-s-new-api-dashboard-data-download-tool-release, last access: 11 November 2023.

QuantAQ: https://quant-aq.com/, last access: 10 March 2024.

Queensland University of Technology - Koala sensors: https://research.qut.edu.au/ilaqh/projects/koala-sensors/, last access: 10 March 2024.

Quevedo, D., Gao, Z., Do, K., Bahreini, R., Collins, D., & Ivey, C.: Multidecadal analysis of meteorological and emissions regimes for pm $_{2.5}$ across california. ACS ES&T Air, 1(1), 33–42. https://doi.org/10.1021/acsestair.3c00019, 2024.

Quintero, E., González, J., García, F., Sáez, Y., & Collado, E.: IoT-based system prototype for particulate matter monitoring in the city of Chitre, Panama. https://laccei.org/LACCEI2023-BuenosAires/meta/FP847.html, 2023.

Raheja, G., Harper, L., Hoffman, A., Gorby, Y., Freese, L., O'Leary, B., Deron, N., Smith, S., Auch, T., Goodwin, M., &

1575   Westervelt, D. M.: Community-based participatory research for low-cost air pollution monitoring in the wake of unconventional oil and gas development in the Ohio River Valley: Empowering impacted residents through community science. Environmental Research Letters, 17(6), 065006. https://doi.org/10.1088/1748-9326/ac6ad6, 2022.

Raheja, G., Sabi, K., Sonla, H., Gbedjangni, E. K., McFarlane, C. M., Hodoli, C. G., & Westervelt, D. M.: A network of field-calibrated low-cost sensor measurements of pm $_{2.5}$ in Lomé, Togo, over one to two years. ACS Earth and Space

1580   Chemistry, 6(4), 1011–1021. https://doi.org/10.1021/acsearthspacechem.1c00391, 2022.

Rai, A. C., Kumar, P., Pilla, F., Skouloudis, A. N., Di Sabatino, S., Ratti, C., Yasar, A., & Rickerby, D.: End-user perspective of low-cost sensors for outdoor air pollution monitoring. Science of The Total Environment, 607–608, 691–705. https://doi.org/10.1016/j.scitotenv.2017.06.266, 2017.

Ramakrishna, J., Durgaprasad, M. B., & Smith, K. R.: Cooking in India: The impact of improved stoves on indoor air

1585   quality. Environment International, 15(1), 341–352. https://doi.org/10.1016/0160-4120(89)90047-0, 1989.

Ren, Y., Qu, Z., Du, Y., Xu, R., Ma, D., Yang, G., Shi, Y., Fan, X., Tani, A., Guo, P., Ge, Y., & Chang, J.: Air quality and health effects of biogenic volatile organic compounds emissions from urban green spaces and the mitigation strategies. Environmental Pollution, 230, 849–861. https://doi.org/10.1016/j.envpol.2017.06.049, 2017.

Ribbit network: https://www.ribbitnetwork.org/, last access: 10 March 2024.

1590   RIVM data portal: https://samenmeten.rivm.nl/dataportaal/, last access: 10 March 2024.

Rodríguez, E. H., Schalm, O., & Martínez, A.: Development of a low-cost measuring system for the monitoring of environmental parameters that affect air quality for human health. ITEGAM-JETIA, 6(22), 22–27. https://itegam-jetia.org/journal/index.php/jetia/article/view/648, 2020.

Rosmarin, A., Curtis, L., & Brown, D. R.: Weather-based evaluation of exposure to airborne toxins to nearby

1595   residents. Environmental Advances, 13, 100415. https://doi.org/10.1016/j.envadv.2023.100415, 2023.

Sablan, O. M., Gargulinski, E., Slater, K., Rosen, Z., Henery, G., Ford, B., Magzamen, S., Soja, A. J., Pierce, J. R., & Fischer, E.: Monitoring smoke from landscape fires in the flint hills region of Kansas during the 2022 burning season. 2022, GH42A-33. https://ui.adsabs.harvard.edu/abs/2022AGUFMGH42A..33S, 2022.

Sahu, R., Dixit, K. K., Mishra, S., Kumar, P., Shukla, A. K., Sutaria, R., Tiwari, S., & Tripathi, S. N.: Validation of low-cost

1600   sensors in measuring real-time pm10 concentrations at two sites in Delhi national capital region. Sensors, 20(5), 1347. https://doi.org/10.3390/s20051347, 2020.

Sahu, R., Nagal, A., Dixit, K. K., Unnibhavi, H., Mantravadi, S., Nair, S., Simmhan, Y., Mishra, B., Zele, R., Sutaria, R., Motghare, V. M., Kar, P., & Tripathi, S. N.: Robust statistical calibration and characterization of portable low-cost air quality monitoring sensors to quantify real-time O_3 and NO_2 concentrations in diverse environments. Atmospheric

1605   Measurement Techniques, 14(1), 37–52. https://doi.org/10.5194/amt-14-37-2021, 2021.

Saleh, T., & Khader, A.: Urban particulate matter hazard mapping and monitoring site selection in Nablus, palestine. Atmosphere, 13(7), 1134. https://doi.org/10.3390/atmos13071134, 2022.

Saúco, L., Pradas, P., Ibarrola, E., Martín, J., & Lardín, C.: Early alert system for odour management in WWTP. 2022 IEEE International Symposium on Olfaction and Electronic Nose (ISOEN), 1–2.

1610   https://doi.org/10.1109/ISOEN54820.2022.9789637, 2022.

Sayahi, T., Garff, A., Quah, T., Lê, K., Becnel, T., Powell, K. M., Gaillardon, P.-E., Butterfield, A. E., & Kelly, K. E.: Long-term calibration models to estimate ozone concentrations with a metal oxide sensor. Environmental Pollution, 267, 115363. https://doi.org/10.1016/j.envpol.2020.115363, 2020.

Sayahi, T., Kaufman, D., Becnel, T., Kaur, K., Butterfield, A. E., Collingwood, S., Zhang, Y., Gaillardon, P.-E., & Kelly, K. E.:

1615   Development of a calibration chamber to evaluate the performance of low-cost particulate matter sensors. Environmental Pollution, 255, 113131. https://doi.org/10.1016/j.envpol.2019.113131, 2019.

Sberveglieri, G., Hellmich, W., & Müller, G.: Silicon hotplates for metal oxide gas sensor elements. Microsystem Technologies, 3(4), 183–190. https://doi.org/10.1007/s005420050078, 1997.

Schalm, O, Carro, G., Lazarov, B., Jacobs, W., Stranger, M.: Reliability of Lower-Cost Sensors in the Analysis of Indoor Air

1620   Quality on Board Ships. Atmosphere, 13, 1579. https://doi.org/10.3390/atmos13101579, 2022.

Shankar, S., Abbas, G., Nithyaprakash, R., Naveenkumar, R., Rakesh Mohanty, S., Sabarinathan, A., & Karthick, S.: Study on the impact of firecrackers on atmospheric pollutants during Diwali festival in Tamil Nadu, India. E3S Web of Conferences, 453, 01004. https://doi.org/10.1051/e3sconf/202345301004, 2023.

Schneider, P., Bartonova, A., Castell, N., Dauge, F.R., Gerboles, M., Hagler, G., Hüglin, C., Jones, R.l., Khan, S., Lewis, A.C., Mijling, B., Müller, M., Penza, M., Spinelle, L., Stacey, B., Vogt, M., Wesseling, J., & Williams, R.W.: Toward a Unified Terminology of Processing Levels for Low-Cost Air-Quality Sensors. Environmental Science and Technology, 53, 15, 8485-8487. https://doi.org/10.1021/acs.est.9b03950, 2019.

Sherwood, R. J., & Greenhalgh, D. M.: A personal air sampler. The Annals of Occupational Hygiene, 2, 127–132. https://doi.org/10.1093/annhyg/2.2.127, 1960.

Shi, Z., Vu, T., Kotthaus, S., Harrison, R. M., Grimmond, S., Yue, S., Zhu, T., Lee, J., Han, Y., Demuzere, M., Dunmore, R. E., Ren, L., Liu, D., Wang, Y., Wild, O., Allan, J., Acton, W. J., Barlow, J., Barratt, B., … Zheng, M.: Introduction to the special issue "In-depth study of air pollution sources and processes within Beijing and its surrounding region (Aphh-beijing)." Atmospheric Chemistry and Physics, 19(11), 7519–7546. https://doi.org/10.5194/acp-19-7519-2019, 2019.

Shibata, K., Yokoo, T., Takeuchi, K., Tanaka, T., Kamino, M., Nishikawa, S., Nakano, S., & Kuwano, Y.: A new-structure ir gas sensor. Japanese Journal of Applied Physics, 26(11R), 1898. https://doi.org/10.1143/JJAP.26.1898, 1987.

Shusterman, A. A., Teige, V. E., Turner, A. J., Newman, C., Kim, J., & Cohen, R. C.: The BErkeley Atmospheric CO_2 Observation Network: Initial evaluation. Atmospheric Chemistry and Physics, 16(21), 13449–13463. https://doi.org/10.5194/acp-16-13449-2016, 2016.

Singh, A., Ng'ang'a, D., Gatari, M. J., Kidane, A. W., Alemu, Z. A., Derrick, N., Webster, M. J., Bartington, S. E., Thomas, G. N., Avis, W., & Pope, F. D.: Air quality assessment in three East African cities using calibrated low-cost sensors with a focus on road-based hotspots. Environmental Research Communications, 3(7), 075007. https://doi.org/10.1088/2515-7620/ac0e0a, 2021.

Sivaraman, V., Carrapetta, J., Hu, K., & Luxan, B. G.: HazeWatch: A participatory sensor system for monitoring air pollution in Sydney. 38th Annual IEEE Conference on Local Computer Networks - Workshops, 56–64. https://doi.org/10.1109/LCNW.2013.6758498, 2013.

Smart Citizen Kit: https://www.seeedstudio.com/Smart-Citizen-Kit-p-2864.html, last access: 10 March 2024.

Soares, A. R., & Silva, C.: Review of ground-level ozone impact in respiratory health deterioration for the past two
decades. Atmosphere, 13(3), 434. https://doi.org/10.3390/atmos13030434, 2022.

Sonkar, S. K., Kumar, P., George, R. C., Philip, D. & Ghosh, A. K.: Detection and Estimation of Natural Gas Leakage Using UAV
1650   by Machine Learning Algorithms. IEEE Sensors Journal, 22, 8. 10.1109/JSEN.2022.3157872, 2022.

Spinelle, L., Aleixandre, M., & Gerboles, M.: Protocol of evaluation and calibration of low-cost gas sensors for the monitoring of
air pollution. JRC Publications Repository. https://doi.org/10.2788/9916, 2013.

Spinelle, L., Gerboles, M., Kok, G., Persijn, S., & Sauerwald, T.: Review of portable and low-cost sensors for the ambient air
monitoring of benzene and other volatile organic compounds. Sensors, 17(7), 1520. https://doi.org/10.3390/s17071520,
1655   2017.

Subramanian, R., Ellis, A., Torres-Delgado, E., Tanzer, R., Malings, C., Rivera, F., Morales, M., Baumgardner, D., Presto, A., &
Mayol-Bracero, O. L.: Air quality in Puerto Rico in the aftermath of hurricane maria: A case study on the use of lower cost
air quality monitors. ACS Earth and Space Chemistry, 2(11), 1179–1186.
https://doi.org/10.1021/acsearthspacechem.8b00079, 2018.

1660 Sun, L., Wong, K. C., Wei, P., Ye, S., Huang, H., Yang, F., Westerdahl, D., Louie, P. K. K., Luk, C. W. Y., & Ning, Z.:
Development and application of a next generation air sensor network for the Hong Kong marathon 2015 air quality
monitoring. Sensors, 16(2), 211. https://doi.org/10.3390/s16020211, 2016.

Sun, Y., Mousavi, A., Masri, S., & Wu, J. Socioeconomic disparities of low-cost air quality sensors in California, 2017–
2020. American Journal of Public Health, 112(3), 434–442. https://doi.org/10.2105/AJPH.2021.306603, 2022.

1665 Suriano, D., Cassano, G., & Penza, M.: A portable gas sensor system for air quality monitoring. In C. Di Natale, V. Ferrari, A.
Ponzoni, G. Sberveglieri, & M. Ferrari (Eds.), Sensors and Microsystems (pp. 155–158). Springer International Publishing.
https://doi.org/10.1007/978-3-319-00684-0_29, 2014.

Suriano, D., Prato, M., Pfister, V., Cassano, G., Dipinto, S., & Penza, M.: 20 - the case-study of the res-novae national project:
Low-cost sensor-systems for urban air quality monitoring. Proceedings, 77–80. https://doi.org/10.5162/6EuNetAir2016/20,
1670   2016.

Tagle, M., Rojas, F., Reyes, F., Vásquez, Y., Hallgren, F., Lindén, J., Kolev, D., Watne, Å. K., & Oyola, P.: Field performance of a low-cost sensor in the monitoring of particulate matter in Santiago, Chile. Environmental Monitoring and Assessment, 192(3), 171. https://doi.org/10.1007/s10661-020-8118-4, 2020.

Tanzer, R., Malings, C., Hauryliuk, A., Subramanian, R., & Presto, A. A.: Demonstration of a low-cost multi-pollutant network to quantify intra-urban spatial variations in air pollutant source impacts and to evaluate environmental justice. International Journal of Environmental Research and Public Health, 16(14), 2523. https://doi.org/10.3390/ijerph16142523, 2019.

Tanzer-Gruener, R., Li, J., Eilenberg, S. R., Robinson, A. L., & Presto, A. A.: Impacts of modifiable factors on ambient air pollution: A case study of covid-19 shutdowns. Environmental Science & Technology Letters, 7(8), 554–559. https://doi.org/10.1021/acs.estlett.0c00365, 2020.

Taylor, J. K.: Sampling and calibration for atmospheric measurements: A symposium sponsored by ASTM committee d-22 on sampling and analysis of atmospheres. ASTM International, 1987.

Tékouabou, S. C. K., Chenal, J., Azmi, R., Diop, E. B., Toulni, H., & Nsegbe, A. de P.: Towards air quality particulate-matter monitoring using low-cost sensor data and visual exploration techniques: Case study of Kisumu, Kenya. Procedia Computer Science, 215, 963–972. https://doi.org/10.1016/j.procs.2022.12.099, 2022.

The world air quality index project - Real-Time Air Quality Sensor Networks: https://aqicn.org/network/, last access: 10 March 2024.

Tryner, J., L'Orange, C., Mehaffy, J., Miller-Lionberg, D., Hofstetter, J. C., Wilson, A., & Volckens, J.: Laboratory evaluation of low-cost PurpleAir PM monitors and in-field correction using co-located portable filter samplers. Atmospheric Environment, 220, 117067. https://doi.org/10.1016/j.atmosenv.2019.117067, 2020.

Tsujita, W., Yoshino, A., Ishida, H., & Moriizumi, T.: Gas sensor network for air-pollution monitoring. Sensors and Actuators B: Chemical, 110(2), 304–311. https://doi.org/10.1016/j.snb.2005.02.008, 2005.

Turner, A. J., Kim, J., Fitzmaurice, H., Newman, C., Worthington, K., Chan, K., Wooldridge, P. J., Köehler, P., Frankenberg, C., & Cohen, R. C.: Observed impacts of covid-19 on urban CO_2 emissions. Geophysical Research Letters, 47(22), e2020GL090037. https://doi.org/10.1029/2020GL090037, 2020.

1695 US EPA - NAAQS Table [Other Policies and Guidance]: https://www.epa.gov/criteria-air-pollutants/naaqs-table, last access: 17

September 2023, 2014.

US EPA Office of Research & Development - Air Sensor Guidebook:

https://cfpub.epa.gov/si/si_public_record_Report.cfm?Lab=NERL&dirEntryId=277996, last access: 7 March 2024.

US EPA Village Green Project - Overviews and Factsheets]: https://www.epa.gov/air-research/village-green-project, last access:

1700   17 September 2023, 2014.

Vajs, I., Drajic, D., & Cica, Z.: Covid-19 lockdown in Belgrade: Impact on air pollution and evaluation of a neural network model

for the correction of low-cost sensors' measurements. Applied Sciences, 11(22), 10563.

https://doi.org/10.3390/app112210563, 2021.

Valenzuela, A. A., Schwab, M., Silnik, A. A., Debattista, A. F., & Kiessling, R. A.: Low power wireless sensor node platform for

1705   agriculture monitoring in Argentina. 2018 International Conference on Cyber-Enabled Distributed Computing and

Knowledge Discovery (CyberC), 101–1014. https://doi.org/10.1109/CyberC.2018.00029, 2018.

Velásquez, R. M. A., Acevedo, D. M. V., Paredes, M. G. S. P., & Vargas, C. Z.: Implementation and analysis of low-cost network

for air pollution in Lima and Arequipa. 2022 IEEE XXIX International Conference on Electronics, Electrical Engineering

and Computing (INTERCON), 1–4. https://doi.org/10.1109/INTERCON55795.2022.9870052, 2022.

1710 Vrijheid, M., Basagaña, X., Gonzalez, J. R., Jaddoe, V. W. V., Jensen, G., Keun, H. C., McEachan, R. R. C., Porcel, J., Siroux, V.,

Swertz, M. A., Thomsen, C., Aasvang, G. M., Andrušaitytė, S., Angeli, K., Avraam, D., Ballester, F., Burton, P.,

Bustamante, M., Casas, M., … Slama, R.: Advancing tools for human early life course exposome research and

translation. Environmental Epidemiology, 5(5), e166. https://doi.org/10.1097/EE9.0000000000000166, 2021.

Wallace, L., Zhao, T., & Klepeis, N. E.: Calibration of purpleair pa-i and pa-ii monitors using daily mean pm2. 5 concentrations

1715   measured in California, Washington, and Oregon from 2017 to 2021. Sensors (Basel, Switzerland), 22(13), 4741.

https://doi.org/10.3390/s22134741, 2022.

Ware, J. H., Spengler, J. D., Neas, L. M., Samet, J. M., Wagner, G. R., Coultas, D., Ozkaynak, H., & Schwab, M.: Respiratory and

irritant health effects of ambient volatile organic compounds. American Journal of Epidemiology, 137(12), 1287–1301.

https://doi.org/10.1093/oxfordjournals.aje.a116639, 1993.

1720 Wen, T.-H., Jiang, J.-A., Sun, C.-H., Juang, J.-Y., & Lin, T.-S.: Monitoring street-level spatial-temporal variations of carbon monoxide in urban settings using a wireless sensor network (Wsn) framework. International Journal of Environmental Research and Public Health, 10(12), 6380–6396. https://doi.org/10.3390/ijerph10126380, 2013.

Weppner, W.: Solid-state electrochemical gas sensors. Sensors and Actuators, 12(2), 107–119. https://doi.org/10.1016/0250-6874(87)85010-2, 1987.

1725 Wesseling, J., de Ruiter, H., Blokhuis, C., Drukker, D., Weijers, E., Volten, H., Vonk, J., Gast, L., Voogt, M., Zandveld, P., van Ratingen, S., & Tielemans, E.: Development and implementation of a platform for public information on air quality, sensor measurements, and citizen science. Atmosphere, 10(8), 445. https://doi.org/10.3390/atmos10080445, 2019.

Whitty, R., Pfeffer, M., Ilyinskaya, E., Roberts, T., Schmidt, A., Barsotti, S., Strauch, W., Crilley, L., Pope, F., Bellanger, H., Mendoza, E., Mather, T., Liu, E., Peters, N., Taylor, I., Francis, H., Hernández Leiva, X., Lynch, D., Nobert, S., & Baxter,

1730 P.: Effectiveness of low-cost air quality monitors for identifying volcanic SO_2 and PM downwind from Masaya volcano, Nicaragua. Volcanica, 5(1), 33–59. https://doi.org/10.30909/vol.05.01.3359, 2022.

Williams, R., Duvall, R., Kilaru, V., Hagler, G., Hassinger, L., Benedict, K., Rice, J., Kaufman, A., Judge, R., Pierce, G., Allen, G., Bergin, M., Cohen, R. C., Fransioli, P., Gerboles, M., Habre, R., Hannigan, M., Jack, D., Louie, P., … Ning, Z.: Deliberating performance targets workshop: Potential paths for emerging PM2.5 and O3 air sensor progress. Atmospheric

1735 Environment: X, 2, 100031. https://doi.org/10.1016/j.aeaoa.2019.100031, 2019.

Windy: https://www.windy.com/, last access: 10 March 2024.

Wyzga, R. E., & Rohr, A. C.: Long-term particulate matter exposure: Attributing health effects to individual PM components. Journal of the Air & Waste Management Association, 65(5), 523–543. https://doi.org/10.1080/10962247.2015.1020396, 2015.

1740 World Meteorological Organization: 2021 WMO Report No. 1215 - An update on low-cost sensors for the measurement of atmospheric composition. ISBN 978-92-63-11215-6. https://library.wmo.int/index.php?id=21508&lvl=notice_display#.Yifnz3yZPIU, 2021.

Xi, X., Johnson, M. S., Jeong, S., Fladeland, M., Pieri, D., Diaz, J. A., & Bland, G. L.: Constraining the sulfur dioxide degassing flux from Turrialba volcano, Costa Rica using unmanned aerial system measurements. Journal of Volcanology and Geothermal Research, 325, 110–118. https://doi.org/10.1016/j.jvolgeores.2016.06.023, 2016.

Yaacoub, E., Kadri, A., Mushtaha, M., & Abu-Dayya, A.: Air quality monitoring and analysis in Qatar using a wireless sensor network deployment. 2013 9th International Wireless Communications and Mobile Computing Conference (IWCMC), 596–601. https://doi.org/10.1109/IWCMC.2013.6583625, 2013.

Yang, L. H., Hagan, D. H., Rivera-Rios, J. C., Kelp, M. M., Cross, E. S., Peng, Y., Kaiser, J., Williams, L. R., Croteau, P. L., Jayne, J. T., & Ng, N. L.: Investigating the sources of urban air pollution using low-cost air quality sensors at an urban Atlanta site. Environmental Science & Technology, 56(11), 7063–7073. https://doi.org/10.1021/acs.est.1c07005, 2022.

Yavus, E., Kuzu, S. L., & Saral, A.: Investigation of vertical particulate matter distribution using low-cost sensors in istanbul, turkey. BL2ES2-21, BABES-21 & BISET-21 Oct. 13-15, 2021 Barcelona (Spain). Oct. 13-15, 2021 Barcelona (Spain). https://doi.org/10.17758/EIRAI10.F1021210, 2021.

Yoo, E.-H., Zammit-Mangion, A., & Chipeta, M. G.: Adaptive spatial sampling design for environmental field prediction using low-cost sensing technologies. Atmospheric Environment, 221, 117091. https://doi.org/10.1016/j.atmosenv.2019.117091, 2020.

Zaidan, M. A., Hossein Motlagh, N., Fung, P. L., Lu, D., Timonen, H., Kuula, J., Niemi, J. V., Tarkoma, S., Petäjä, T., Kulmala, M., & Hussein, T.: Intelligent calibration and virtual sensing for integrated low-cost air quality sensors. IEEE Sensors Journal, 20(22), 13638–13652. https://doi.org/10.1109/JSEN.2020.3010316, 2020.

Zaldei, A., Vagnoli, C., Di Lonardo, S., Gioli, B., Gualtieri, G., Toscano, P., Martelli, F., & Matese, A.: AIRQino, a low-cost air quality mobile platform. 6158. https://ui.adsabs.harvard.edu/abs/2015EGUGA..17.6158Z, 2015.

Zampolli, S., Elmi, I., Ahmed, F., Passini, M., Cardinali, G. C., Nicoletti, S., & Dori, L.: An electronic nose based on solid state sensor arrays for low-cost indoor air quality monitoring applications. Sensors and Actuators B: Chemical, 101(1–2), 39–46. https://doi.org/10.1016/j.snb.2004.02.024, 2004.

Zeb, A., Soininen, J.-P., & Sozer, N.: Data harmonisation as a key to enable digitalisation of the food sector: A review. Food and Bioproducts Processing, 127, 360–370. https://doi.org/10.1016/j.fbp.2021.02.005, 2021.

Zhou, F., Liu, J., Zhu, H., Yang, X., Fan, Y.: A Real-Time Measurement-Modeling System for Ship Air Pollution Emission Factors. J. Mar. Sci. Eng. 10(6), 760, https://doi.org/10.3390/jmse10060760, 2022.

1770 Zimmerman, N., Presto, A. A., Kumar, S. P. N., Gu, J., Hauryliuk, A., Robinson, E. S., Robinson, A. L., & R. Subramanian.: A machine learning calibration model using random forests to improve sensor performance for lower-cost air quality monitoring. Atmospheric Measurement Techniques, 11(1), 291–313. https://doi.org/10.5194/amt-11-291-2018, 2018.