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Seasonal effects in the application of the MOMA remote calibration tool to outdoor $PM_{2.5}$ air sensors

Lena F. Weissert[1], Geoff S. Henshaw[1], Andrea L. Clements[2], Rachelle M. Duvall[2], and Carry Croghan[2]

[1]Aeroqual Ltd, 460 Rosebank Road, Avondale, Auckland, 1026, New Zealand; lena.weissert@aeroqual.com (L.W.); geoff.henshaw@aeroqual.com (G.H.)

[2]U.S. Environmental Protection Agency, Office of Research and Development, Center for Environmental Measurement and Modelling, 109 T.W. Alexander Drive, P.O. Box 12055, Research Triangle Park, NC 27711; clements.andrea@epa.gov (A.C.); duvall.rachelle@epa.gov (R.D.); croghan.carry@epa.gov (C.C.)

Correspondence to: Lena F. Weissert (lena.weissert@aeroqual.com)

Abstract. Air sensors are being used more frequently to measure hyper-local air quality. The PurpleAir sensor is among one of the most popular air sensors used worldwide to measure fine particulate matter ($PM_{2.5}$). However, there is a need to understand PurpleAir data quality especially under different environmental conditions with varying particulate matter (PM) sources and size distributions. Several correction factors have been developed to make the PurpleAir sensor data more comparable to reference monitor data. The goal of this work was to determine the performance of a remote calibration tool called MOment MAtching (MOMA) for temporally varying $PM_{2.5}$ sources. MOMA performs calibrations using reference site data within 0-15 km from the sensor. Data from 20 PurpleAir sensors deployed across a network in Phoenix, Arizona from July 2019 to April 2021 were used. The results showed that the MOMA calibration tool improved the accuracy of PurpleAir sensor data across Phoenix and was comparable to the EPA correction factor with a root mean square error (RMSE) of 4.19 – 7.92 µg m^{-3} vs. 4.23 – 9.27 µg m^{-3}. However, MOMA provided a better estimate of daily exceedances compared to the reference data for smoke conditions. Using speciated PM data, MOMA was able to distinguish between different PM sources such as winter wood burning, and wildfires and dust events in the summer.

Key Words. Fine particulate matter, air sensors, PurpleAir, correction factors, MOMA, speciated PM

1 Introduction

Exposure to fine particulate matter ($PM_{2.5}$, particles 2.5 µm in diameter and smaller) is linked to several adverse health effects. Due to its small size, $PM_{2.5}$ has the ability to penetrate deep into the lung and spread to the whole body resulting in cardio-

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pulmonary disorder and adverse birth outcomes as well as contributing to the development of diabetes and antibiotic resistance (World Health Organization, 2023; Feng et al., 2016; Zhou et al., 2023). Studies have shown that even at low levels (below the U.S. National Ambient Air Quality Standards or NAAQS) $PM_{2.5}$ can be a significant health risk (Elliott and Copes, 2011; Fann et al., 2012). Thus, there is a need to measure air pollution at a high spatial and temporal resolution to understand localized air quality in areas where people live, work, commute, and play (English et al., 2017). Data from lower-cost air sensors have great potential to provide such insights helping communities to minimize exposure to unhealthy air pollution (Ardon-Dryer et al., 2019; Castell et al., 2017; Snyder et al., 2013; Stavroulas et al., 2020).

The Plantower PMS 5003 (PMS) sensor, used in the PurpleAir sensor, is amongst the most popular lower-cost sensors to measure particulate matter (PM) concentrations with thousands of sensors deployed globally providing publicly available data in real-time (https://www2.purpleair.com/). The PMS sensor reports particle counts between 0.3 and 10 µm across six size bins and provides mass concentration estimates for PM_1 (particles < 1 µm in diameter), $PM_{2.5}$, and PM_{10} (particles < 10 µm in diameter). Numerous studies have investigated the performance of PurpleAir sensors in the field across the United States (Ardon-Dryer et al., 2019; Barkjohn et al., 2021a; Feenstra et al., 2019; Jaffe et al., 2023; Malings et al., 2020; Ouimette et al., 2022; Sayahi et al., 2019; Tryner et al., 2020b) and other parts of the world (e.g., Greece (Kosmopoulos et al., 2022; Stavroulas et al., 2020), Australia (Robinson, 2020)) as well as in the laboratory (Kuula et al., 2020; Tryner et al., 2020b). While these studies showed that the PurpleAir sensors are precise and linearly related to $PM_{2.5}$ reference data up to approximately 250 µg/m^3, they are not always accurate (Barkjohn et al., 2022). In particular, results suggest that the PurpleAir sensor response decreases with increasing particle size and is mostly insensitive to particles > 1 µm (Ouimette et al., 2022). Thus, concerns about the data quality in particular under different environmental conditions with varying PM sources and size distributions remain (Barkjohn et al., 2021a; Jaffe et al., 2023; Ouimette et al., 2022; Williams, 2019).

As a result, recent work has focused on developing correction algorithms for PurpleAir sensors (Ardon-Dryer et al., 2019; Barkjohn et al., 2021a; Holder et al., 2020; Magi et al., 2020). A U.S.-wide correction algorithm developed by the U.S. Environmental Protection Agency's (EPA) showed significant improvements in accuracy across several regions and conditions (Barkjohn et al., 2021a). The algorithm was further developed (Barkjohn et al., 2021b) and is now implemented in the AirNow Fire and Smoke map (https://fire.airnow.gov/). Despite the extensive dataset used in this study the authors mention that further analysis may be required to test the performance of their correction long-term as well as for extreme events and regions that were under-sampled but are characterized by different $PM_{2.5}$ sources (i.e., southern parts of the U.S., Northern Rockies, Ohio Valley). A recent study evaluating the performance of the correction for dust, wildfire, and urban pollution suggested that the accuracy of the PMS using the EPA correction varies for different pollution types (Jaffe et al., 2023). Additionally, the study found that the correction was not able to account for missed particles associated with dust events and underestimated the reference $PM_{2.5}$ by a factor of 5-6.

Wallace et al. (2022) developed a method to calculate $PM_{2.5}$ estimates from the particle count data and then established calibration factors using reference sites within 500 m of the PurpleAir sensor for comparison. However, lower-cost sensors are often deployed in areas lacking monitoring data and consequently reference monitors are further away.

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In the following work, we use a remote calibration tool, called MOment MAtching (MOMA), to calibrate PurpleAir sensors deployed in Phoenix, Arizona. MOMA uses data from distant reference sites (within 0 – 15 km), referred to as 'proxies', to determine if a sensor has drifted and to calculate the calibration gain and offset, referred to as MOMA gain and offset. MOMA is based on the assumption that data from the reference site shows statistical similarity to those of the sensor site for a period of time representative of the regional pollutant variation (Miskell et al., 2018, 2019; Weissert et al., 2020). MOMA has been tested extensively in the Southern California region for ozone (O_3), nitrogen dioxide (NO_2), $PM_{2.5}$, and PM_{10} concentrations from Aeroqual sensors (AQY, v1.0, Aeroqual Ltd, Auckland, New Zealand) (Miskell et al., 2019; Weissert et al., 2020, 2023). Southern California is characterized by a Mediterranean climate with hot, mostly dry summers and mild winters. While Phoenix, Arizona also experiences hot and dry summers, winter nighttime temperatures can go below freezing and smoke related to wood burning is a common source of PM pollution, worsened by Phoenix surrounding mountains which limit vertical mixing of air pollutants (Grineski et al., 2007). In addition, Phoenix typically experiences 2 – 4 dust storms during its monsoon season (June – September). The most intense dust storms, known as haboobs, move over Phoenix as a wall of dust and may decrease the visibility to less than 1 km (Eagar et al., 2017).

The primary aim of this paper was to determine the performance of MOMA for temporally varying pollution sources. Originally, MOMA was developed to correct sensor data associated with instrumental drift which was defined as drift lasting for several days. However, previous research suggested that the MOMA calibration gain reflected changes in PM composition associated with different PM sources which can vary temporally from a few hours to days (Weissert et al., 2023). Therefore, we are specifically interested in determining if a) MOMA can give insights into PM sources, and b) if MOMA is able to detect sensor drift associated with different PM sources. The MOMA results are compared to the EPA correction (Barkjohn et al., 2021b).

2 Methods

2.1 Datasets

2.1.1 $PM_{2.5}$ data

To better understand local air pollution associated with wood burning, Maricopa County and the U.S. EPA deployed a network of PurpleAir PA-II sensors across the Phoenix, Arizona Region between 2019 – 2021. From this network, we used data from 4 sites co-located with reference monitors (Mesa, Durango, South Phoenix, West Phoenix) and 16 other sites with non-co-located PurpleAir sensors deployed across Phoenix (Fig. 1). The network data are available from July 2019 – April 2021.

The PurpleAir PA-II contains two PMS sensors, referred to as 'Channel A' and 'Channel B'. The PMS sensor mass concentrations are either reported as cf_1 or cf_atm ('atmosphere'). For this analysis we use 'cf_atm' data. PurpleAir raw data were reported at 2 min intervals and averaged to hourly values when data completeness for each hour was >75%. Hourly data from Channel A and Channel B were compared and data were removed when the difference between Channel A and B

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was > 70% and >5 µg/m^3 (Barkjohn et al., 2021a; Collier-Oxandale et al., 2022). The average $PM_{2.5}$ concentration from Channel A and Channel B was used for this analysis.

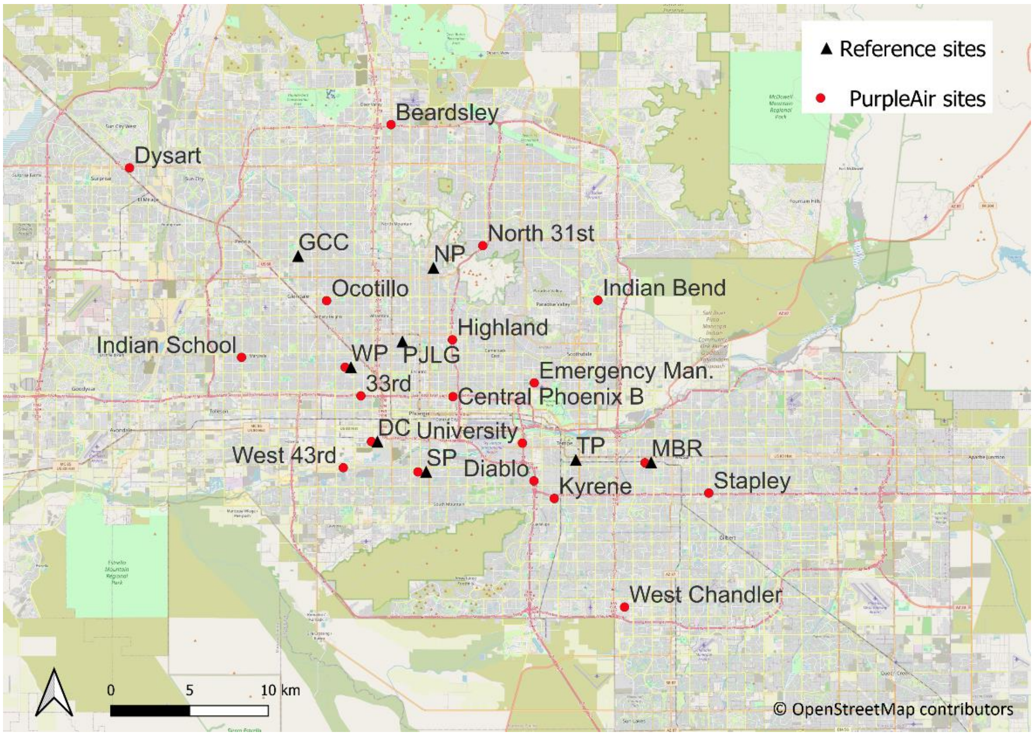

Figure 1. Map of PurpleAir sites and Reference sites in Phoenix. The full names of the reference sites are shown in Table 1. The map was created using the Free and Open Source QGIS.

Hourly $PM_{2.5}$ reference data were accessed via AirNow (https://gispub.epa.gov/airnow/) (Figure 1). The reference network consisted of 1 Beta Attenuation Monitor (BAM) (BAM 1020, Met One Instruments, Inc., Grants Pass, Oregon, U.S.) at Phoenix JLG Supersite and 8 dichotomous Taper Element Oscillating Microbalance (TEOM) monitors (TEOM 1405-DF, Thermo Scientific, Waltham, MA, U.S.). For comparison, we also used hourly $PM_{2.5}$ reference data from a reference grade optical instrument – T640x (Teledyne API, San Diego, U.S.), which was deployed at West Phoenix from November 2018 until April 2021.

2.1.2 Supporting data

To determine if we can relate detected PM events to different PM sources, we used speciation data collected at JLG Supersite and accessed via RAQSAPI package (Mccrowey et al., 2022), which allows downloading monitoring data from the U.S. EPA Air Quality System service. We focused on parameters representing crustal material (Fe, Mg, Si, K), trace ions (K^+, Na, Cl^-),

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secondary ions (NH_4^+, NO_3^-, SO_4^{2-}), elemental carbon (EC), and organic carbon (OC) following the PM source classification described in Weissert et al. (2023). Surface meteorological data from the Phoenix Sky Harbor International Airport were downloaded from the NOAA Integrated Surface Database (ISD) via the worldmet Package in R (Carslaw, 2022).

2.2 Proxy selection

We selected proxies based on results from Weissert et al. (2023) which suggested that the nearest proxy (0 – 15 km) is generally a suitable choice for $PM_{2.5}$. For co-located sites, we used the co-location reference as a proxy while the nearest proxy was selected for PurpleAir sensors deployed at sites with no reference data (Table 1).

Table 1. Sensor site and the nearest proxy as well as the distance to the nearest proxy.

Sensor site	Distance to nearest Proxy (km)	Nearest Proxy
West Phoenix	0	West Phoenix - WP
Durango	0	Durango Complex - DC
Mesa	0	Mesa - Brooks Reservoir - MBR
South Phoenix	0	South Phoenix - SP
33rd	2.8	West Phoenix - WP
West 43rd	3.3	Durango Complex - DC
Kyrene	3.5	Tempe - TP
Diablo	3.6	Tempe - TP
University	4.3	Tempe - TP
Highland	4.8	Phoenix JLG Supersite - PJLG
Ocotillo	4.8	Glendale Community College - GCC
North 31st	5.1	North Phoenix -NP
Stapley	6.1	Mesa - Brooks Reservoir - MBR
Central Phoenix B	6.7	Phoenix JLG Supersite - PJLG
Emergency Management	7.2	Tempe - TP
Indian School	8.9	West Phoenix - WP
West Chandler	12.5	Mesa - Brooks Reservoir - MBR
Beardsley	12.6	North Phoenix - NP
Indian Bend	13.9	Tempe - TP
Dysart	15.8	Glendale Community College - GCC

2.3 MOMA

PurpleAir data were corrected using our previously published MOMA calibration tool to detect sensor drift and apply a correction (Miskell et al., 2018, 2019; Weissert et al., 2020, Weissert et al., 2023). In brief, MOMA uses a two-sample Kolmogorov-Smirnov (K-S) test and the mean, E-variance, var (MV) moment-matching MOMA gain, $\hat{a}_1$ and the intercept,

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$\hat{a}_0$ to determine if sensor data, Y at location i have drifted in relation to the proxy data, Z at location k over the time interval $t - t_d\!:t$.

$$\hat{a}_1 = \sqrt{var\{Z_{k,t-t_d:t}\}/var\{Y_{i,t-t_d:t}\}} \quad (1)$$

$$\hat{a}_0 = E\{Z_{k,t-t_d:t}\} - \hat{a}_1 E\{Y_{i,t-t_d:t}\} \quad (2)$$

We used the following thresholds to determine sensor drift: K-S test p-value < 0.05, 0.75 > $\hat{a}_1$> 1.25; -5 µg m^{-3} > $\hat{a}_0$ > 5 µg m^{-3}. We used a 3-day rolling average to calculate the statistics and a correction was triggered when any of the three statistics exceeded the threshold for a period of 4 consecutive days. Given that we test the performance of MOMA for PM sources that may vary at shorter or longer timescales, we compare the MOMA corrected results from the 4-day threshold to those obtained using a 3-day threshold and 5-day threshold. The impact of this threshold was tested using Purple Air data from South Phoenix, West Phoenix, and Durango and calibrating these against the nearest proxy reference, to represent the impact of calibrating against a distant proxy reference. The calibrated data were then compared against the co-located reference.

2.4 U.S.-wide Purple Air correction

To compare the results from MOMA we also applied the piecewise regression used for the AirNow Fire and Smoke Map to the PurpleAir data (Barkjohn et al., 2021b):

if $0 <= x < 30$:

$$y = 0.524x - 0.0862 \times \mathrm{RH} + 5.75 \quad (3)$$

if $30 <= x < 50$:

$$y = (0.786 \times (x/20 - 3/2) + 0.524 \times (1 - (x/20 - 3/2))) \times x - 0.0862 \times \mathrm{RH} + 5.75 \quad (4)$$

if $50 <= x < 210$:

$$y = 0.786x - 0.0862 \times \mathrm{RH} + 5.75 \quad (5)$$

if $210 <= x < 260$:

$$y = (0.69x \times (x/50 - 2/5) + 0.786 \times (1 - (x/50 - 21/5))) \times x - 0.0862 \times \mathrm{RH} \times (1 - (x/50 - 21/5)) + 2.966 \times (x/50 - 21/5) + 5.75 \times (1 - (x/50 - 21/5)) + 8.84 \times 10^{-4} \times x^2 \times (x/50 - 21/5) \quad (6)$$

if $x >= 260$:

$$y = 2.966 + 0.69 \times x + 8.84 \times 10^{-4} \times x^2 \quad (7)$$

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Where x is cf_atm (μg m^{-3}) and RH is relative humidity (%).

2.5 PM$_{2.5}$ source identification

Previous research suggested that the sensor-proxy relationship changes are associated with differences in PM sources and composition (Tryner et al., 2020; Jaffe et al., 2023; Ouimette et al., 2022; Weissert et al., 2023). Thus, we use the temporal variation of the MOMA gain, $\hat{a}_1$ (Eq. 1), calculated over a 3-day rolling window (t_d) to identify conditions when PurpleAir sensors tend to over- or under-estimate PM$_{2.5}$ concentrations compared to the reference data.

We assume that differences in the MOMA gain are related to the presence of different PM sources characterized by a different size distribution. In particular, we focused on distinguishing between smoke and dust and general urban traffic PM sources. These sources are common in Phoenix and are associated with different particle sizes and composition (Jaffe et al., 2023). We averaged the MOMA gain for each day and across the whole network to identify days dominated by smoke, dust, and typical urban PM sources. We then tested the performance of MOMA and the EPA correction under these different conditions.

3 Results and Discussion

3.1 Seasonal effects and PM source identification

The temporal variation of the MOMA gains for each sensor is shown in Figure 2. The step changes indicate when the drift detection test triggered a MOMA calibration indicating more frequent corrections over the summer months (e.g., West Phoenix). Unlike most other sites, the drift detection test triggered frequent alarms at 33rd across the whole study period despite being close to the proxy site (2.8 km). Mean uncorrected PM$_{2.5}$ concentrations at 33rd were 4 μg m^{-3}, less than half of those recorded at West Phoenix (10 μg m^{-3}), despite being located next to a busy motorway, indicating a potential sensor or siting issue at this site. Similarly, Dysart resulted in frequent calibrations which is likely a result of an unsuitable proxy given the site is located north of Phoenix the furthest away from any reference site (> 15 km) and selected as a background site.

Similar to previous findings (Weissert et al. 2023), the temporal variation of the MOMA gain indicates a change in PM source with a seasonal pattern. It is evident that the PurpleAir sensors tend to under-estimate over the summer (MOMA gain > 1) and over-estimate during the winter months (MOMA gain < 1) (Fig. 2).

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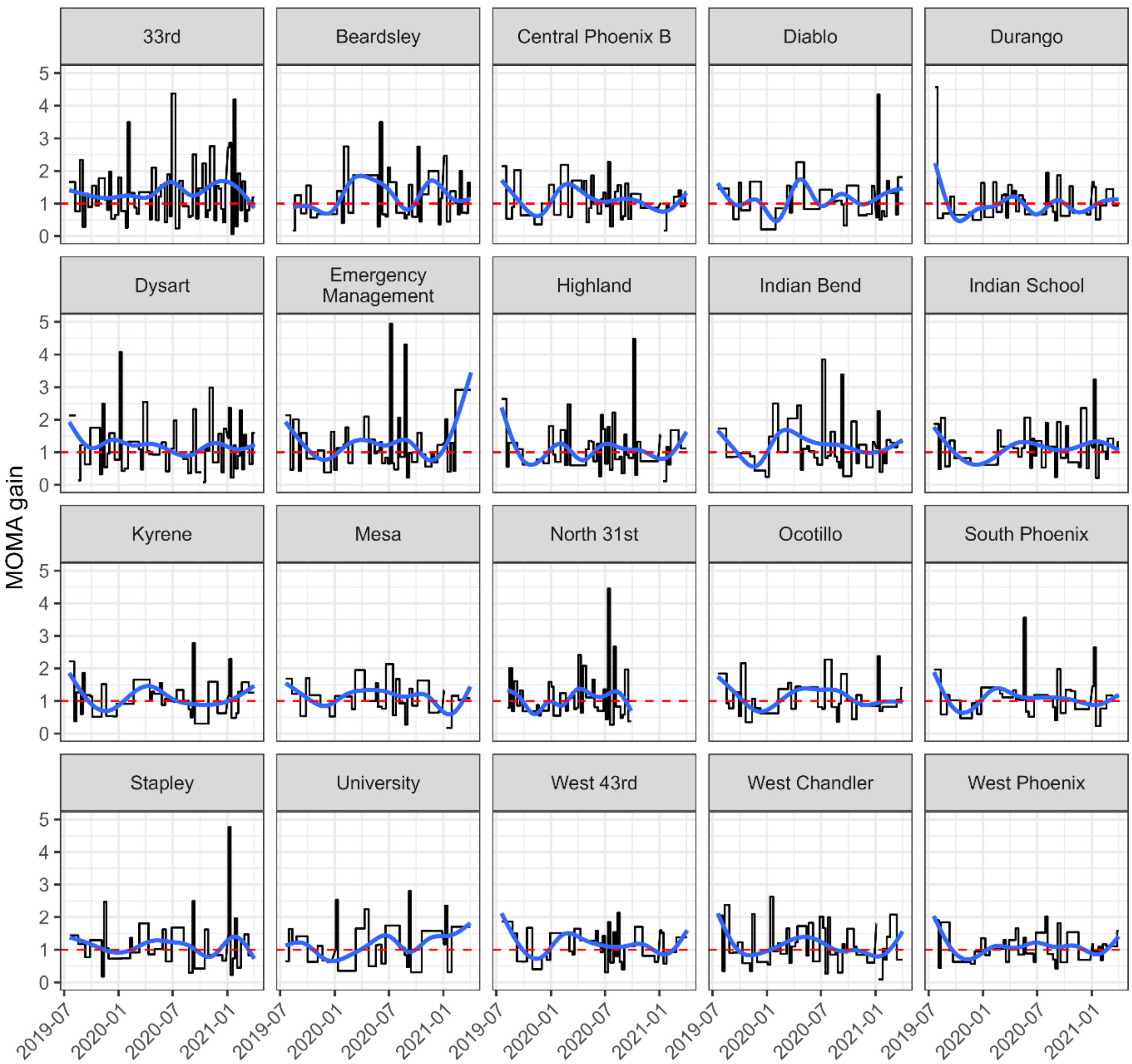

Figure 2. Temporal variation of the MOMA gain from July 2019 - April 2021. Step changes refer to a change in the gain; the smooth curve represents the overall temporal trend of the gains.

MOMA only triggers a calibration when a sensor shows statistical difference for a continuous period of 4 days. While this is suitable for long lasting pollution events or instrumental sensor drift, it risks missing short-term events such as dust storms or PM sources that show diurnal variations such as wood smoke related to domestic heating. Thus, the 3-day rolling MOMA gain from July 2019 – April 2021, shown in Figure 3, provides more detailed insights into the temporal variability of PM sources

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independent of the drift detection framework. Figure 3 clearly shows the observed MOMA gain < 1 for PurpleAir sensors during the winter and occasionally during the summer (e.g., August/September 2020). The difference between the PurpleAir sensor and the reference data varies diurnally over winter with the largest differences observed at nighttime. Two factors may contribute to the PurpleAir sensors over-estimating in winter at nighttime. First, RH is higher at nighttime which can lead to hygroscopic growth of particles impacting the light scattering (Badura et al., 2018; Morawska et al., 2018). Second, other research (e.g., Jaffe et al., 2023; Barkjohn et al., 2021a; Holder et al., 2020; Tryner et al., 2020a) found that PurpleAir sensors over-estimated in the presence of smoke particles and typical secondary urban aerosols and it is possible that wood smoke, a dominant $PM_{2.5}$ source in winter in Phoenix (Ramadan et al., 2000) is further contributing to a lower MOMA gain. In contrast, there are periods (mostly between June and September) when the PurpleAir under-estimates compared to the proxy reference (MOMA gain > 2.5) (Figure 3). These periods were generally short and easily seen as $PM_{2.5}$ spikes in the reference data as well as a reduction in visibility measured at the Airport. However, this was not observed in the sensor concentrations (e.g., August 16/17, 2020). According to White et al. (2023) a major dust storm was recorded in National Oceanic and Atmospheric Administration (NOAA) Storm Event Database on August 16, 2020 in Maricopa agreeing with the spike from the reference data (White et al., 2023). Shortly after the dust event the 3-day rolling MOMA gain was < 1 and likely reflecting the presence of wildfire smoke from one of California's worst wildfire seasons (Keeley and Syphard, 2021).

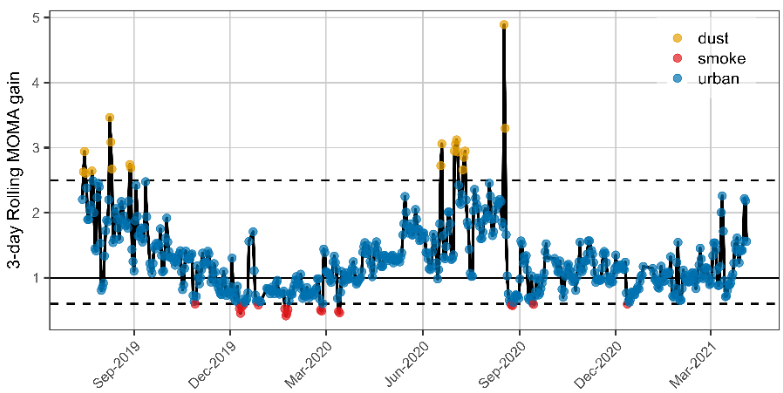

Figure 3. Daily averaged 3-day rolling MOMA gain averaged across the entire sensor network from July 2019 - April 2021.

Given our findings, we separated our dataset into $PM_{2.5}$ categories of smoke (MOMA gain ≤ 0.6) and dust conditions (MOMA gain > 2.5) with the remaining data considered to be typical urban $PM_{2.5}$ (traffic, industrial). This resulted in 20 dust days (all in summer) and 18 smoke days (winter: 12, spring: 2, summer: 2, fall: 2) between July 2019 and April 2021. Figure 4 shows the $PM_{2.5}/PM_{10}$ ratio for each $PM_{2.5}$ source category. As expected, smoke days were associated with a higher $PM_{2.5}/PM_{10}$ ratio

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indicative of a high fine particle ($PM_{2.5}$) fraction, and characterised by higher concentrations of EC and OC compared to the other two categories (Tong et al., 2012). Dust days, on the other hand, had larger particles ($PM_{2.5}$/PM10 ratio <0.3) and higher concentrations of crustal elements. These results are in agreement with ratios (0.15 – 0.26) used by the US EPA for fugitive dust particles (Midwest Research Institute (MRI), 2005) and other studies (Tong et al., 2012: <0.35 for dust in western U.S., Sandhu et al., 2024: 0.23 for dust days in the greater Phoenix area).

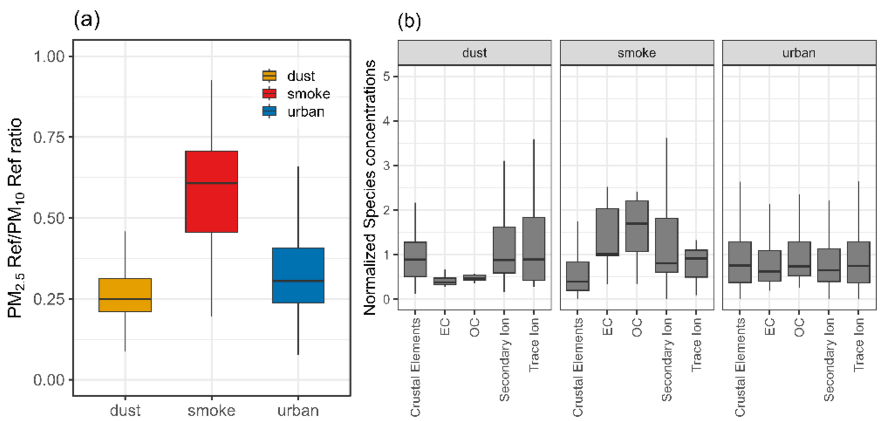

Figure 4. a) $PM_{2.5}$/PM_{10} reference ratio measured across the AirNow reference network grouped by the three $PM_{2.5}$ source categories, and b) normalized species concentrations measured for the three different $PM_{2.5}$ source categories.

3.2 Performance of MOMA under different conditions

Figure 5 shows the co-located reference data against the PurpleAir data without any correction (a), with the EPA correction (b), and the MOMA calibration (c) for data from the four co-location sites (Durango Complex, West Phoenix, South Phoenix, Mesa). As previously observed (Barkjohn et al., 2021a; Holder et al., 2020; Jaffe et al., 2023), uncorrected PurpleAir sensor data correlated well with the co-located reference data as indicated by the high R^2 (0.80) for winter smoke and typical urban conditions but over-estimated $PM_{2.5}$ at higher concentrations when smoke particles are present and RH is high. As expected, the relationship between the PurpleAir sensors and the co-located reference is poorer during dust conditions (R^2 = 0.53) and the PurpleAir sensors under-estimated $PM_{2.5}$. Both the EPA correction and the MOMA calibration resulted in improved accuracy for all source categories as indicated by a reduction in the mean absolute error (MAE). However, neither the EPA correction nor the drift calibration framework were able to fully correct for the missed dust particles at high concentrations and the root mean square error (RMSE) remained high. This was also observed in Fig. 6 which shows uncorrected, MOMA calibrated and EPA corrected data from August 2020 when a dust event (Fig. 6a) moved over Phoenix followed by wildfire smoke (Fig. 6b). Both the MOMA calibrated data and the EPA corrected data missed the dust spike but performed well during

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the wildfire event. In contrast, the T640x detected the dust event indicating it is sensitive to the larger dust particles. This highlights the limitations of the design of the lower cost PM sensor in the PurpleAir sensor which is insensitive to crustal dust (Jaffe et al., 2023; He et al., 2020; Ouimette et al., 2022; Kuula et al., 2020). This may be due to poor transport of larger particles into its optical cavity and/or poor light scattering design (Kuula et al., 2020). In contrast, during the wildfire episode (Fig. 6b) both the T640x and the PurpleAir sensors showed a positive bias versus the TEOM. This is well known for PurpleAir sensors (Barkjohn et al., 2021a; Jaffe et al., 2023) and has also been observed for the T640x (Barkjohn et al., 2021b; Long et al., 2023).

Overall, MOMA performed similar to the EPA correction in terms of MAE (2.48 – 3.07 µg m^{-3} vs. 2.69 – 3.75 µg m^{-3}, respectively) and RMSE (4.19 – 7.92 µg m^{-3} vs. 4.23 – 9.27 µg m^{-3}, respectively) (Fig. 5). However, MOMA performed slightly better at correcting for outliers and therefore compared better to the reference in terms of detecting the number of daily National Ambient Air Quality Standard (NAAQS) exceedances during smoke conditions (Table 2). Neither correction resulted in an improvement in the R^2.

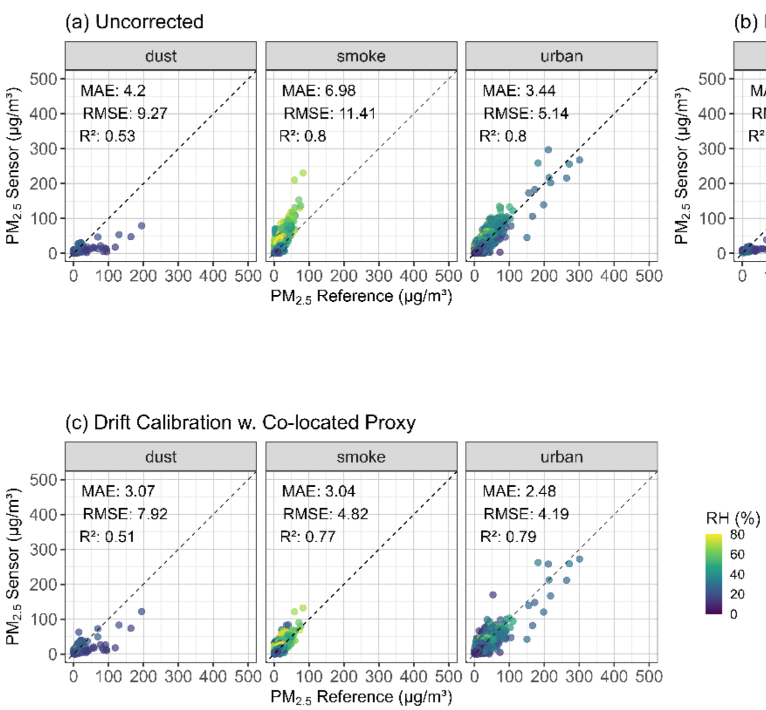

Figure 5. Hourly sensor measurements compared to reference data at the 4 co-location sites for a) uncorrected (‘PM25_atm’) PM$_{2.5}$ sensor data, b) corrected sensor data using the EPA correction, and c) MOMA calibrated sensor data during different conditions identified using the 3-day rolling MOMA gain. Points are coloured by RH (%).

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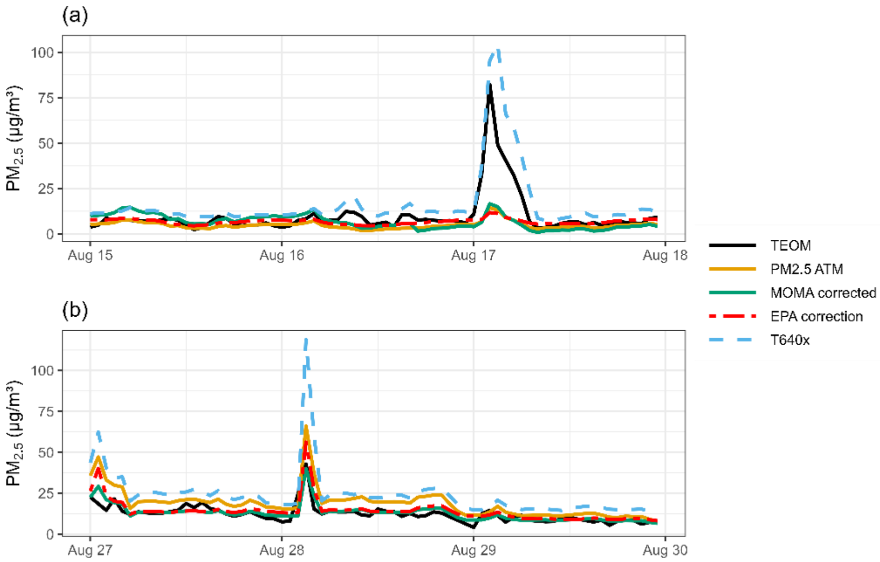

Figure 6. $PM_{2.5}$ concentrations measured at West Phoenix by the co-located TEOM and T640x reference and the PurpleAir Sensor (uncorrected 'PM25 ATM'), with the EPA correction and MOMA applied during the a) dust event, and b) the wildfire smoke conditions.

Table 2. Nr. of daily exceedances (NAAQS: > 35 µg m^{-3}) detected by the co-located PurpleAir sensors when using uncorrected, MOMA calibrated, and the EPA corrected data across different PM sources.

	PurpleAir Sensors			
PM source	**Uncorrected**	**MOMA**	**EPA correction**	**Reference**
Dust	0	0	0	0
Smoke	20	1	5	0
Urban	21	6	7	4

Table 3 shows a comparison of the MAE for MOMA with a 4-day (used throughout this paper), 3-day, and 5-day threshold to raise a drift alarm for each PM source at the co-location sites. The length of the window used to trigger a calibration is a trade-off between over-correction and removal of local effects (shorter window), particularly when calibrating against a distant proxy, and minimising the response time if a sensor is drifting (longer window). This is reflected in Table 3, which shows best improvements with a 4-day threshold and a decrease in the improvement of the MAE using a shorter or longer window to trigger a calibration. This was observed across all sites, however the improvement was slightly better at West Phoenix and South Phoenix compared to Durango. Durango is located next to the City of Phoenix Transfer Station, a rubbish collection

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site, and the pollutant sources as well as temporal variations may therefore be different from those observed at its proxy site South Phoenix, which is representative of a residential area. However, overall differences are small and the length of window to trigger an alarm may also depend on the PM source and its spatial variability.

Table 3. Average percent improvement in the MAE before ($PM_{2.5}$ ATM) and after the MOMA calibration for different drift detection thresholds measured for Purple Air sensors at the co-location sites West Phoenix, South Phoenix, and Durango. Data were calibrated against the nearest reference site and results compared to the co-located reference. These thresholds determine when a drift alarm is raised (i.e., the number of consecutive days a warning needs to be exceeded for before a correction is triggered).

	% improvement in the MAE		
PM source	**3 days**	**4 days**	**5 days**
Dust	24	26	24
Smoke	50	53	50
Urban	19	22	18

4 Conclusions

This paper provided insights into the performance of the MOMA remote calibration tool and the EPA correction for PurpleAir sensors and highlighted challenges related to calibrating PM sensors for seasonally and diurnally varying PM sources. MOMA improved the accuracy of the PurpleAir data resulting in a similar hourly MAE as the EPA correction. The MOMA gain also provided a simple method of distinguishing between different PM sources such as wood burning in winter and wildfires and dust events in summer. This may help identify PM sources based on sensor-reference relationships adding further value to PurpleAir sensor networks. However, further analysis is required to test the application of this classification across other climate regions in the US or worldwide and to refine thresholds used to classify dust and smoke events.

We have highlighted the challenges in the calibration of PurpleAir sensors for Phoenix conditions in which the magnitude and sources of $PM_{2.5}$ vary. The EPA correction is independent from reference sites and works well for smoke dominated conditions but poorly for dust events. MOMA, being a dynamic method, is better at accommodating PM source variations and performed better in estimating the number of daily NAAQS exceedances but rapid, short-term changes such as dust events and diurnally varying woodsmoke patterns can be challenging. In addition, MOMA is dependent on reliable proxy reference sites within 15 km to the sensor site representative of average pollution sources present at the sensor site.

The comparison between the TEOM and T640x monitor during the wildfire and dust storm events demonstrated that differences among the EPA correction and the MOMA calibration are observed even between the regulatory methods.

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References

Ardon-Dryer, K., Dryer, Y., Williams, J. N., and Moghimi, N.: Measurements of $PM_{2.5}$ with PurpleAir under atmospheric conditions, Aerosols/In Situ Measurement/Instruments and Platforms, https://doi.org/10.5194/amt-2019-396, 2019.

Badura, M., Batog, P., Drzeniecka-Osiadacz, A., and Modzel, P.: Evaluation of Low-Cost Sensors for Ambient $PM_{2.5}$ Monitoring, J. Sens., 2018, 1–16, https://doi.org/10.1155/2018/5096540, 2018.

Barkjohn, K. K., Gantt, B., and Clements, A. L.: Development and application of a United States-wide correction for $PM_{2.5}$ data collected with the PurpleAir sensor, Atmospheric Meas. Tech., 14, 4617–4637, https://doi.org/10.5194/amt-14-4617-2021, 2021a.

https://doi.org/10.5194/egusphere-2024-3454
Preprint. Discussion started: 15 November 2024

Barkjohn, K. K., Holder, A. L., Clements, A. L., Frederick, Samuel, and Evans, Ron: Sensor Data Cleaning and Correction: Application on the AirNow Fire and Smoke Map, American Association for Aerosol Research, 2021b.

Barkjohn, K. K., Holder, A. L., Frederick, S. G., and Clements, A. L.: Correction and Accuracy of PurpleAir $PM_{2.5}$ Measurements for Extreme Wildfire Smoke, Sensors, 22, 9669, https://doi.org/10.3390/s22249669, 2022.

Carslaw, D.: worldmet: Import Surface Meteorological Data from NOAA Integrated Surface Database (ISD), 2022.

Castell, N., Dauge, F. R., Schneider, P., Vogt, M., Lerner, U., Fishbain, B., Broday, D., and Bartonova, A.: Can commercial low-cost sensor platforms contribute to air quality monitoring and exposure estimates?, Environ. Int., 99, 293–302, https://doi.org/10.1016/j.envint.2016.12.007, 2017.

Collier-Oxandale, A., Feenstra, B., Papapostolou, V., and Polidori, A.: AirSensor v1.0: Enhancements to the open-source R package to enable deep understanding of the long-term performance and reliability of PurpleAir sensors, Environ. Model. Softw., 148, 105256, https://doi.org/10.1016/j.envsoft.2021.105256, 2022.

Eagar, J. D., Herckes, P., and Hartnett, H. E.: The characterization of haboobs and the deposition of dust in Tempe, AZ from 2005 to 2014, Aeolian Res., 24, 81–91, https://doi.org/10.1016/j.aeolia.2016.11.004, 2017.

Elliott, C. T. and Copes, R.: Burden of mortality due to ambient fine particulate air pollution ($PM_{2.5}$) in interior and Northern BC., Can. J. Public Health Rev. Can. Sante Publique, 102, 390–393, https://doi.org/10.1007/BF03404182, 2011.

English, P. B., Olmedo, L., Bejarano, E., Lugo, H., Murillo, E., Seto, E., Wong, M., King, G., Wilkie, A., Meltzer, D., Carvlin, G., Jerrett, M., and Northcross, A.: The Imperial County Community Air Monitoring Network: A Model for Community-based Environmental Monitoring for Public Health Action, Environ. Health Perspect., 125, 074501, https://doi.org/10.1289/EHP1772, 2017.

Fann, N., Lamson, A. D., Anenberg, S. C., Wesson, K., Risley, D., and Hubbell, B. J.: Estimating the national public health burden associated with exposure to ambient $PM_{2.5}$ and ozone., Risk Anal. Off. Publ. Soc. Risk Anal., 32, 81–95, https://doi.org/10.1111/j.1539-6924.2011.01630.x, 2012.

Feenstra, B., Papapostolou, V., Hasheminassab, S., Zhang, H., Boghossian, B. D., Cocker, D., and Polidori, A.: Performance evaluation of twelve low-cost $PM_{2.5}$ sensors at an ambient air monitoring site, Atmos. Environ., 216, 116946, https://doi.org/10.1016/j.atmosenv.2019.116946, 2019.

Feng, S., Gao, D., Liao, F., Zhou, F., and Wang, X.: The health effects of ambient $PM_{2.5}$ and potential mechanisms, 2016, 128, 67–74, n.d.

Grineski, S., Bolin, B., and Boone, C.: Criteria Air Pollution and Marginalized Populations: Environmental Inequity in Metropolitan Phoenix, Arizona n, Soc. Sci. Q., 2007.

He, M., Kuerbanjiang, N., and Dhaniyala, S.: Performance characteristics of the low-cost Plantower PMS optical sensor, Aerosol Sci. Technol., 54, 232–241, https://doi.org/10.1080/02786826.2019.1696015, 2020.

Holder, A. L., Mebust, A. K., Maghran, L. A., McGown, M. R., Stewart, K. E., Vallano, D. M., Elleman, R. A., and Baker, K. R.: Field Evaluation of Low-Cost Particulate Matter Sensors for Measuring Wildfire Smoke, Sensors, 20, 4796, https://doi.org/10.3390/s20174796, 2020.

https://doi.org/10.5194/egusphere-2024-3454
Preprint. Discussion started: 15 November 2024

Jaffe, D. A., Miller, C., Thompson, K., Finley, B., Nelson, M., Ouimette, J., and Andrews, E.: An evaluation of the U.S. EPA's correction equation for PurpleAir sensor data in smoke, dust, and wintertime urban pollution events, Atmospheric Meas. Tech., 16, 1311–1322, https://doi.org/10.5194/amt-16-1311-2023, 2023.

Keeley, J. E. and Syphard, A. D.: Large California wildfires: 2020 fires in historical context, Fire Ecol., 17, 22, https://doi.org/10.1186/s42408-021-00110-7, 2021.

Kosmopoulos, G., Salamalikis, V., Matrali, A., Pandis, S. N., and Kazantzidis, A.: Insights about the Sources of $PM_{2.5}$ in an Urban Area from Measurements of a Low-Cost Sensor Network, Atmosphere, 13, 440, https://doi.org/10.3390/atmos13030440, 2022.

Kuula, J., Mäkelä, T., Aurela, M., Teinilä, K., Varjonen, S., González, Ó., and Timonen, H.: Laboratory evaluation of particle-size selectivity of optical low-cost particulate matter sensors, Atmospheric Meas. Tech., 13, 2413–2423, https://doi.org/10.5194/amt-13-2413-2020, 2020.

Long, R. W., Urbanski, S. P., Lincoln, E., Colón, M., Kaushik, S., Krug, J. D., Vanderpool, R. W., and Landis, M. S.: Summary of $PM_{2.5}$ measurement artifacts associated with the Teledyne T640 PM Mass Monitor under controlled chamber experimental conditions using polydisperse ammonium sulfate aerosols and biomass smoke, J. Air Waste Manag. Assoc., 73, 295–312, https://doi.org/10.1080/10962247.2023.2171156, 2023.

Magi, B. I., Cupini, C., Francis, J., Green, M., and Hauser, C.: Evaluation of $PM_{2.5}$ measured in an urban setting using a low-cost optical particle counter and a Federal Equivalent Method Beta Attenuation Monitor, Aerosol Sci. Technol., 54, 147–159, https://doi.org/10.1080/02786826.2019.1619915, 2020.

Malings, C., Tanzer, R., Hauryliuk, A., Saha, P. K., Robinson, A. L., Presto, A. A., and Subramanian, R.: Fine particle mass monitoring with low-cost sensors: Corrections and long-term performance evaluation, Aerosol Sci. Technol., 54, 160–174, https://doi.org/10.1080/02786826.2019.1623863, 2020.

Mccrowey, C., Sharac, T., Mangus, N., Jager, D., Brown, R., Garver, D., Wells, B., and Brittingham, H.: RAQSAPI: A Simple Interface to the US EPA Air Quality System Data Mart API, 2022.

Midwest Research Institute (MRI): Analysis of the Fine Fraction of Particulate Matter in Fugitive Dust - Final Report, 2005.

Miskell, G., Salmond, J. A., and Williams, D. E.: Solution to the Problem of Calibration of Low-Cost Air Quality Measurement Sensors in Networks, ACS Sens., 3, 832–843, https://doi.org/10.1021/acssensors.8b00074, 2018.

Miskell, G., Alberti, K., Feenstra, B., Henshaw, G. S., Papapostolou, V., Patel, H., Polidori, A., Salmond, J. A., Weissert, L., and Williams, D. E.: Reliable data from low cost ozone sensors in a hierarchical network, Atmos. Environ., 214, 116870, https://doi.org/10.1016/j.atmosenv.2019.116870, 2019.

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., Mullins, B., Rahman, M. M., Ristovski, Z., Shafiei, M., Tjondronegoro, D., Westerdahl, D., and Williams, R.: Applications of low-cost sensing technologies for air quality monitoring and exposure assessment: How far have they gone?, Environ. Int., 116, 286–299, https://doi.org/10.1016/j.envint.2018.04.018, 2018.

Ouimette, J. R., Malm, W. C., Schichtel, B. A., Sheridan, P. J., Andrews, E., Ogren, J. A., and Arnott, W. P.: Evaluating the PurpleAir monitor as an aerosol light scattering instrument, Atmospheric Meas. Tech., 15, 655–676, https://doi.org/10.5194/amt-15-655-2022, 2022.

Ramadan, Z., Song, X.-H., and Hopke, P. K.: Identification of Sources of Phoenix Aerosol by Positive Matrix Factorization, J. Air Waste Manag. Assoc., 50, 1308–1320, https://doi.org/10.1080/10473289.2000.10464173, 2000.

Robinson, D. L.: Accurate, Low Cost PM2.5 Measurements Demonstrate the Large Spatial Variation in Wood Smoke Pollution in Regional Australia and Improve Modeling and Estimates of Health Costs, Atmosphere, 11, 856, https://doi.org/10.3390/atmos11080856, 2020.

Sandhu, T., Robinson, M. C., Rawlins, E., and Ardon-Dryer, K.: Identification of dust events in the greater Phoenix area, Atmospheric Pollut. Res., 15, 102275, https://doi.org/10.1016/j.apr.2024.102275, 2024.

Sayahi, T., Butterfield, A., and Kelly, K. E.: Long-term field evaluation of the Plantower PMS low-cost particulate matter sensors, Environ. Pollut., 245, 932–940, https://doi.org/10.1016/j.envpol.2018.11.065, 2019.

Snyder, E. G., Watkins, T. H., Solomon, P. A., Thoma, E. D., Williams, R. W., Hagler, G. S. W., Shelow, D., Hindin, D. A., Kilaru, V. J., and Preuss, P. W.: The Changing Paradigm of Air Pollution Monitoring, Environ. Sci. Technol., 47, 11369–11377, https://doi.org/10.1021/es4022602, 2013.

Stavroulas, I., Grivas, G., Michalopoulos, P., Liakakou, E., Bougiatioti, A., Kalkavouras, P., Fameli, K., Hatzianastassiou, N., Mihalopoulos, N., and Gerasopoulos, E.: Field Evaluation of Low-Cost PM Sensors (Purple Air PA-II) Under Variable Urban Air Quality Conditions, in Greece, Atmosphere, 11, 926, https://doi.org/10.3390/atmos11090926, 2020.

Tong, D. Q., Dan, M., Wang, T., and Lee, P.: Long-term dust climatology in the western United States reconstructed from routine aerosol ground monitoring, Atmospheric Chem. Phys., 12, 5189–5205, https://doi.org/10.5194/acp-12-5189-2012, 2012.

Tryner, J., Mehaffy, J., Miller-Lionberg, D., and Volckens, J.: Effects of aerosol type and simulated aging on performance of low-cost PM sensors, J. Aerosol Sci., 150, 105654, https://doi.org/10.1016/j.jaerosci.2020.105654, 2020a.

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

Weissert, L., Miles, E., Miskell, G., Alberti, K., Feenstra, B., Henshaw, G. S., Papapostolou, V., Patel, H., Polidori, A., Salmond, J. A., and Williams, D. E.: Hierarchical network design for nitrogen dioxide measurement in urban environments, Atmos. Environ., 228, 117428, https://doi.org/10.1016/j.atmosenv.2020.117428, 2020.

Weissert, L. F., Henshaw, G. S., Williams, D. E., Feenstra, B., Lam, R., Collier-Oxandale, A., Papapostolou, V., and Polidori, A.: Performance evaluation of MOMA (MOment MAtching) – a remote network calibration technique for $PM_{2.5}$ and PM_{10} sensors, Atmospheric Meas. Tech., 16, 4709–4722, https://doi.org/10.5194/amt-16-4709-2023, 2023.

White, J. R., Balling, R. C., and Cerveny, R. S.: Trajectory analysis of central Sonoran Desert dust storms, J. Arid Environ., 219, 105077, https://doi.org/10.1016/j.jaridenv.2023.105077, 2023.

Williams, D. E.: Low Cost Sensor Networks: How Do We Know the Data Are Reliable?, ACS Sens., 4, 2558–2565, https://doi.org/10.1021/acssensors.9b01455, 2019.

World Health Organization: Ambient (outdoor) air pollution, 2023.

Zhou, Z., Shuai, X., Lin, Z., Yu, X., Ba, X., Holmes, M. A., Xiao, Y., Gu, B., and Chen, H.: Association between particulate matter $PM_{2.5}$ air pollution and clinical antibiotic resistance: a global analysis, Lancet Planet. Health, 7, e649–e659, https://doi.org/10.1016/S2542-5196(23)00135-3, 2023.