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

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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 PM$_{2.5}$ sensors monitoring near temporally varying pollution sources of PM$_{2.5}$. 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. Results showed that the MOMA calibration tool made the PurpleAir PM$_{2.5}$ data more comparable to the co-located reference data (calibrated Mean Absolute Error (MAE): 2.8 – 3.7 µg m^{-3}, Mean Bias Error (MBE): -1.8 – 0.1 µg m^{-3}). The improvements were comparable to the Environmental Protection Agency (EPA) correction factor (MAE: 2.8 – 3.7 µg m^{-3}, MBE: -0.9 – 0.4 µg m^{-3}). However, MOMA provided a better estimate of daily average concentrations than the EPA correction factor when compared to the reference data under smoke conditions. Using the MOMA gain, representative of the sensor-proxy relationship, MOMA was able to distinguish between PM sources such as winter wood burning, 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 adverse health effects. This is particularly well-documented for PM$_{2.5}$, with causal relationships established between both short- and long-term exposure and respiratory, cardiovascular, and total mortality (U.S. EPA, 2019). Evidence also suggests that PM$_{2.5}$ poses a significant health risk even at low concentrations with no 'safe' threshold (Elliott and Copes, 2011; Fann et al., 2012; U.S. EPA, 2019). 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, Plantower Technology, China) sensor, used in the PurpleAir sensor, is amongst the most popular lower-cost sensor used to measure particulate matter (PM) concentrations. There are thousands of PurpleAir sensors deployed globally providing publicly available data in real-time (https://map.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 < 1µm in diameter), PM$_{2.5}$ and PM$_{10}$ (particles < 10µm in diameter). Numerous studies have investigated the performance of PurpleAir sensors in the field across the United States (U.S., Ardon-Dryer et al., 2019; Barkjohn et al., 2021; 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). The measurement range of PurpleAir sensors is notated to be from 0.3 – 10 µm, however, results suggest that the PurpleAir sensor is most responsive to particles between 0.4 and 1 µm (Ouimette et al., 2024, 2022). Thus, concerns about the data quality in particular under different environmental conditions with varying PM sources and size distributions remain (Barkjohn et al., 2021; 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., 2021; Holder et al., 2020; Magi et al., 2020; Wallace et al., 2021, 2022). 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., 2021). The algorithm was further developed (Barkjohn et al., 2022) 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 Environmental Protection Agency (EPA) correction varies for different pollution types (Jaffe et al., 2023). Additionally, the study found that the correction was not able to account for

64 missed particles associated with dust events and underestimated the reference $PM_{2.5}$ by a factor of 5-6. Wallace et al. (2022)

65 developed a method to calculate $PM_{2.5}$ estimate from the particle count data and then established calibration factors using

66 reference sites within 500 m of the PurpleAir sensor for comparison. However, lower cost sensors are often deployed in areas

67 lacking monitoring data and consequently reference monitors are further away.

68 In the following work, we use a remote calibration tool, called MOment MAtching (MOMA), to calibrate PurpleAir sensors

69 deployed in Phoenix, Arizona. MOMA uses data from distant reference sites (within 0 – 15 km), referred to as 'proxies', to

70 determine if a sensor has drifted and to calculate the calibration gain and offset, referred to as MOMA gain and offset. MOMA

71 is based on the assumption that data from the reference site shows statistical similarity to those of the sensor site for a period

72 of time representative of the regional pollutant variation (Miskell et al., 2018, 2019; Weissert et al., 2020). MOMA has been

73 tested extensively in the Southern California region for ozone (O_3), nitrogen dioxide (NO_2), $PM_{2.5}$, and PM_{10} concentrations

74 from Aeroqual sensors (AQY, v1.0, Aeroqual Ltd, Auckland, New Zealand) (Miskell et al., 2019; Weissert et al., 2020, 2023).

75 Southern California is characterized by a Mediterranean climate with hot, mostly dry summers and mild winters. While

76 Phoenix, Arizona also experiences hot and dry summers, winter nighttime temperatures can go below freezing and smoke

77 related to wood burning is a common source of PM pollution, worsened by Phoenix's surrounding mountains which limit

78 vertical mixing of air pollutants (Grineski et al., 2007). In addition, Phoenix typically experiences 2 – 4 dust storms during its

79 monsoon season (June – September). The most intense dust storms, known as haboobs, move over Phoenix as a wall of dust

80 and may decrease the visibility to less than 1 km (Eagar et al., 2017).

81 The primary aim of this paper was to determine the performance of MOMA for $PM_{2.5}$ air sensors monitoring near temporally

82 varying pollution sources. Originally, MOMA was developed to correct sensor data associated with instrumental drift which

83 was defined as drift lasting for several days. However, previous research suggested that the MOMA calibration gain reflected

84 changes in PM composition associated with different PM sources which can vary temporally from a few hours to days

85 (Weissert et al., 2023). Therefore, we are specifically interested in determining if a) MOMA can give insights into PM sources,

86 and b) if MOMA is able to detect sensor drift associated with different PM sources. The MOMA results are compared to the

87 EPA correction (Barkjohn et al., 2022).

88 **2 Methods**

89 **2.1 Datasets**

90 **2.1.1 $PM_{2.5}$ data**

91 To better understand local air pollution associated with wood burning, Maricopa County and the U.S. EPA deployed a network

92 of PurpleAir PA-II sensors across the Phoenix, Arizona Region between 2019 – 2021. From this network, we used data from

93 four sites co-located with reference monitors (Mesa – Brooks Reservoir, Durango Complex, South Phoenix, West Phoenix)

and 16 other sites with non-co-located PurpleAir sensors deployed across Phoenix (Figure 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 hourly percentage difference between Channel A and B was > 70% and > 5 µg/m^3 (Barkjohn et al., 2021; Collier-Oxandale et al., 2022). The average PM$_{2.5}$ concentration from Channel A and Channel B was used for this analysis.

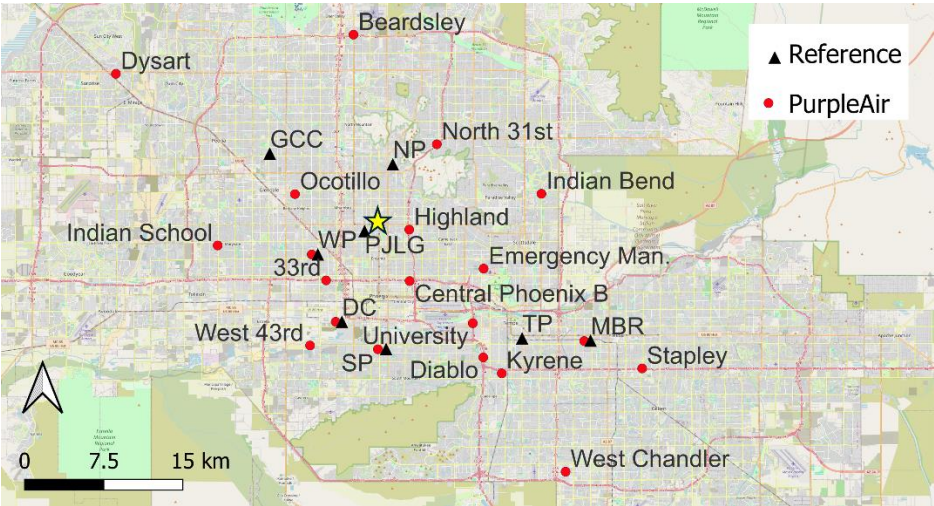



Figure 1. Map of PurpleAir sites and Reference sites in Phoenix. The speciation data were collected at PJLG, highlighted by the yellow star. The full names of the reference sites are shown in Table 1. The map was created using the Free and Open Source QGIS.

Hourly PM$_{2.5}$ reference data were accessed via AirNow (https://gispub.epa.gov/airnow/) (Figure 1). The reference network consisted of one Beta Attenuation Monitor (BAM) (BAM 1020, Met One Instruments, Inc., Grants Pass, Oregon, U.S.) at PJLG Supersite and seven dichotomous Taper Element Oscillating Microbalance (TEOM) monitors (TEOM 1405-DF, Thermo Scientific, Waltham, MA, U.S.). PurpleAir data were calibrated against the BAM and TEOM reference monitors. In addition, we 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 (the T640x data are not reflective of the April 2023 firmware update that implemented an alignment factor). The T640x data were used to assess whether the relationships observed between PurpleAir sensors and BAM/TEOM reference monitors across different PM sources also apply when using an optical reference instrument, they were not used to calibrate the sensor data at West Phoenix.

118 **2.1.2 Supporting data**

119 To determine if we can relate detected PM events to different PM sources, we used speciation data collected every third day

120 at the PJLG Supersite (PJLG, Figure 1) and accessed via RAQSAPI package (McCrowey et al., 2022), which allows

121 downloading monitoring data from the U.S. EPA Air Quality System (AQS) service. We focused on parameters representing

122 crustal material (iron [Fe], magnesium [Mg], silicon [Si], potassium [K]), trace ions (potassium ion [K^+], sodium ion [Na^+],

123 chloride [Cl^-]), secondary ions (ammonium [NH_4^+], nitrate [NO_3^-], sulfate [SO_4^{2-}]) elemental carbon (EC), and organic carbon

124 (OC) following the PM source classification described in Weissert et al. (2023). Surface meteorological data from the Phoenix

125 Sky Harbor International Airport were downloaded from the National Oceanic and Atmospheric Administration (NOAA)

126 Integrated Surface Database (ISD) via the worldmet Package in R (Carslaw, 2022).

127

128 **2.2 Proxy selection**

129 We selected proxies based on results from Weissert et al. (2023) which suggested that the nearest proxy (0 – 15 km) is generally

130 a suitable choice for $PM_{2.5}$ (Table 1). The nearest proxy for the co-located sensor sites was between 5 – 6.5 km away from the

131 sensor site and therefore representative of the sensor-proxy distance of most sites.

132

133 **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	Co-located Proxy
West Phoenix	5.0	Phoenix JLG Supersite - PJLG	West Phoenix - WP
Durango Complex	4.9	South Phoenix - SP	Durango Complex - DC
Mesa – Brooks Reservoir	6.5	Tempe - TP	Mesa - Brooks Reservoir - MBR
South Phoenix	4.9	Durango Complex - DC	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	

134

2.3 MOMA

136 PurpleAir data were corrected using our previously published MOMA calibration tool to detect sensor drift and apply a
137 correction (Miskell et al., 2018, 2019; Weissert et al., 2020, Weissert et al., 2023). In brief, MOMA uses a two-sample
138 Kolmogorov-Smirnov (K-S) test and the mean, E, -variance, var, (Mean-Variance, M-V) moment-matching MOMA gain, $\hat{a}_1$
139 and the intercept, $\hat{a}_0$ to determine if sensor data, Y at location i, have drifted in relation to the proxy data, Z at location k, over
140 the time interval $t - t_d:t$.

141

142 $\hat{a}_1 = \sqrt{var\{Z_{k,t-t_d:t}\}/var\{Y_{i,t-t_d:t}\}}$ $\hspace{2cm}$ (Eq. 1)

143 $\hat{a}_0 = E\{Z_{k,t-t_d:t}\} - \hat{a}_1 E\{Y_{i,t-t_d:t}\}$ $\hspace{2cm}$ (Eq. 2)

144

145 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
146 m^{-3}. We used a 3-day rolling average to calculate the statistics and a correction, as shown in Eq. 3, was triggered when any of
147 the three statistics exceeded the threshold for a period of four consecutive days. The correction was applied retroactively to
148 the start of this 4-day period.

149

150 $\hat{C}_{PM_{2.5}} = \hat{a}_0 + \hat{a}_1 Y_{i,t}$ $\hspace{2cm}$ (Eq. 3)

151

152 Subsequent corrections are only applied if the corrected PM$_{2.5}$, $\hat{C}_{PM_{2.5}}$, have drifted in comparison to the proxy data. Given that
153 we test the performance of MOMA for PM sources that may vary at shorter or longer timescales, we compare the MOMA
154 corrected results from the 4-day threshold to those obtained using a 3-day threshold and 5-day threshold.
155 The performance of the MOMA calibration tool was tested using PurpleAir data from South Phoenix, West Phoenix, Durango
156 Complex and Mesa – Brooks Reservoir calibrated against the nearest proxy reference to represent the impact of calibrating
157 against a distant proxy reference. The calibrated data were then compared against the co-located reference.

158

2.4 U.S.-wide PurpleAir correction

160 To compare the results from MOMA we also applied the piecewise regression used for the AirNow Fire and Smoke Map to
161 the PurpleAir data (Barkjohn et al., 2022):

162

163 if $0 <= x < 30$:

164 $$y = 0.524x - 0.0862 \times RH + 5.75 \qquad \text{(Eq. 4)}$$

165 if $30 \leq x < 50$:

166 $$y = (0.786 \times (x/20 - 3/2) + 0.524 \times (1 - (x/20 - 3/2))) \times x - 0.0862 \times RH + 5.75 \qquad \text{(Eq. 5)}$$

167 if $50 \leq x < 210$:

168 $$y = 0.786x - 0.0862 \times RH + 5.75 \qquad \text{(Eq. 6)}$$

169 if $210 \leq x < 260$:

170 $$y = (0.69x \times (x/50 - 21/5) + 0.786 \times (1 - (x/50 - 21/5))) \times x - 0.0862 \times RH \times (1 - (x/50 - 21/5)) + 2.966 \times$$

171 $$(x/50 - 21/5) + 5.75 \times (1 - (x/50 - 21/5)) + 8.84 \times 10^{-4} \times x^2 \times (x/50 - 21/5) \qquad \text{(Eq. 7)}$$

172 if $x \geq 260$:

173 $$y = 2.966 + 0.69 \times x + 8.84 \times 10^{-4} \times x^2 \qquad \text{(Eq. 8)}$$

174

175

176 Where x is cf_atm (µg m^{-3}) and RH is relative humidity (%) measured by the PurpleAir Sensors.

177

2.5 PM$_{2.5}$ source identification

179 Previous research suggested that the sensor-proxy relationship changes are associated with differences in PM sources and

180 composition (Tryner et al., 2020; Jaffe et al., 2023; Ouimette et al., 2022; Weissert et al., 2023). Thus, we use the temporal

181 variation of the MOMA gain, $\hat{a}_1$ (Eq. 1), calculated over a 3-day rolling window (t_d) to identify conditions when PurpleAir

182 sensors tend to over- or underestimate PM$_{2.5}$ concentrations compared to the reference data. This MOMA gain is representative

183 of the proxy relationship relative to the uncorrected PurpleAir data and independent of sensor drift alarms. The proxies outlined

184 in Table 1 were also used to calculate the 3-day rolling MOMA gain.

185 We assume that differences in the MOMA gain are, to some extent, related to the presence of different PM sources

186 characterized by a different size distribution, chemical properties, or optical properties. In particular, we focused on

187 distinguishing between smoke, dust, and general urban traffic PM sources. These sources are common in Phoenix and are

188 associated with different particle sizes and composition (Jaffe et al., 2023). We averaged the MOMA gain for each day to

189 identify days dominated by smoke, dust, and typical urban PM sources. We then tested the performance of MOMA and the

190 EPA correction under these different conditions.

3 Results and Discussion

3.1 Seasonal effects and PM source identification

Figure 2 shows the monthly variations of the MOMA gain used to correct the PurpleAir sensor data across the whole dataset and the number of drift alarms raised at each site. Figure 2a indicates that the MOMA calibration gain represents monthly variations that are more consistent with changes in PM sources rather than with instrumental drift. 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 across the whole study period at 33rd were 4 µg m^{-3}, less than half of those recorded at West Phoenix (10 µg m^{-3}). Low concentrations at 33rd were surprising given the site is located next to a busy motorway, indicating a potential sensor or siting issue for a $PM_{2.5}$ measurement at this site (Figure S1). Alternatively, frequent alarms could signify an unsuitable proxy match due to different particle sources. The 33rd site is influenced predominantly by vehicle traffic and the West Phoenix site is influenced by the residential community surrounding the site with particle sources like lower-speed road dust, cooking emissions, and residential smoke (e.g., domestic heating, backyard fire pits). 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.

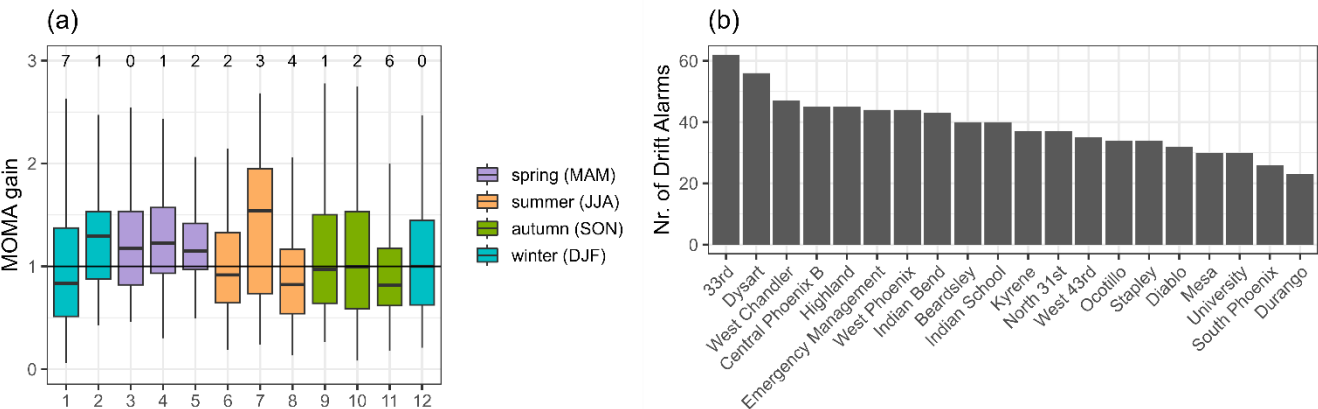



Figure 2. a) Boxplot showing the monthly variations of the MOMA gain from the drift detection framework used to correct the PurpleAir sensor data across the whole network coloured by season. The numbers at the top indicate the number of outliers observed for different months, b) Bar chart showing the number of drift alarms and calibrations triggered at each site.

MOMA only triggers a calibration when a sensor shows a statistical difference for a continuous period of four 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. Additionally, the MOMA gain

215 produced by the calibration tool and shown in Figure 2a is calculated relative to the previously applied MOMA gain and offset,
216 meaning it reflects changes in the sensor-proxy relationship based on prior corrections rather than an absolute comparison to
217 the proxy reference. Thus, the 3-day rolling MOMA gain from July 2019 – April 2021, shown in Figure 3a, provides more
218 detailed insights into the temporal variability of PM sources independent of the drift detection framework and representative
219 of the relationship between the uncorrected PurpleAir data and the proxy reference data. Figure 3a clearly shows the observed
220 MOMA gain < 1 for PurpleAir sensors during the winter and occasionally during the summer (e.g., August/September 2020),
221 suggesting PurpleAir sensors overestimate $PM_{2.5}$ compared to the proxy reference under these conditions. Two factors may
222 contribute to the PurpleAir sensors overestimating in winter, particularly at night and in the early morning hours (8 pm – 7 am,
223 Figure S2). First, RH is higher at night as well as during winter (Figure 3b), which can lead to hygroscopic growth of particles
224 impacting the light scattering (Badura et al., 2018; Morawska et al., 2018). Second, other research (e.g., Jaffe et al., 2023;
225 Barkjohn et al., 2021a; Holder et al., 2020; Tryner et al., 2020a) found that PurpleAir sensors overestimated in the presence of
226 smoke particles and typical secondary urban aerosols. The difference between the PurpleAir sensor and the reference data
227 varies diurnally over winter with the largest differences observed at night and in the early morning (Figure S2). Wood burning
228 is more popular during winter evening recreation. It is therefore possible that wood smoke, a dominant $PM_{2.5}$ source in winter
229 in Phoenix (Ramadan et al., 2000), accumulates at night and that colder nighttime temperatures and overnight winter inversions
230 can lower the mixing height thereby trapping emissions and elevating $PM_{2.5}$ concentrations contributing to a lower MOMA
231 gain in winter. In contrast, there are periods (most frequently in July and August) when the PurpleAir sensors underestimate
232 compared to the proxy reference (MOMA gain > 2.5) (Figure 3). These periods were generally short and easily seen as $PM_{2.5}$
233 spikes in the reference data as well as a reduction in visibility measured at the airport. According to White et al. (2023) a major
234 dust storm was recorded in the NOAA Storm Event Database on August 16, 2020 in Maricopa agreeing with the spike from
235 the reference data (White et al., 2023). However, this was not observed in the sensor concentrations (e.g., August 16-17, 2020)
236 consistent with previous findings that PurpleAir sensors underestimate $PM_{2.5}$ concentrations during dust events due to the
237 narrower particle size range detected (Ouimette et al., 2022; Stavroulas et al., 2020). Shortly after the dust event the 3-day
238 rolling MOMA gain was < 1 in September 2020 and likely reflecting the presence of wildfire smoke from one of California's
239 worst wildfire seasons (Keeley and Syphard, 2021).

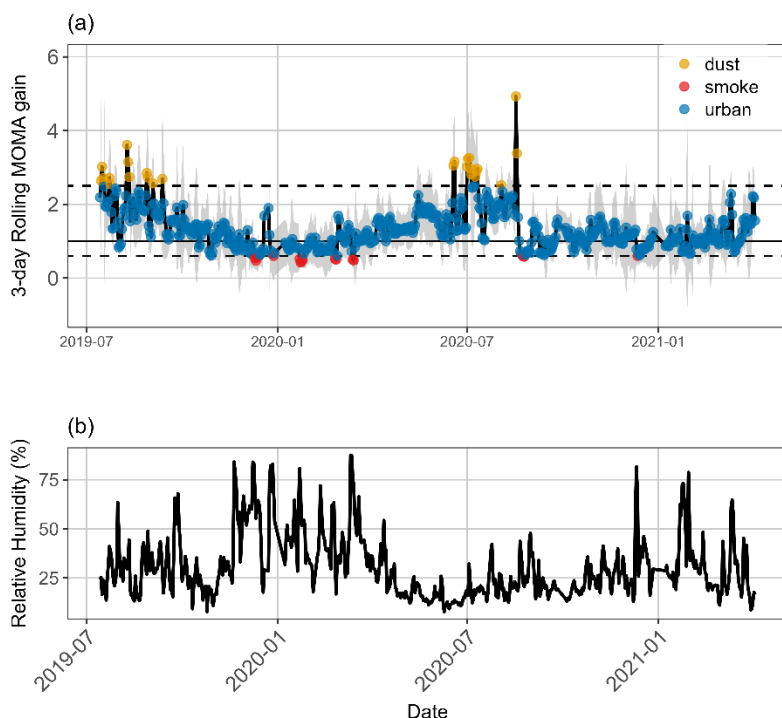
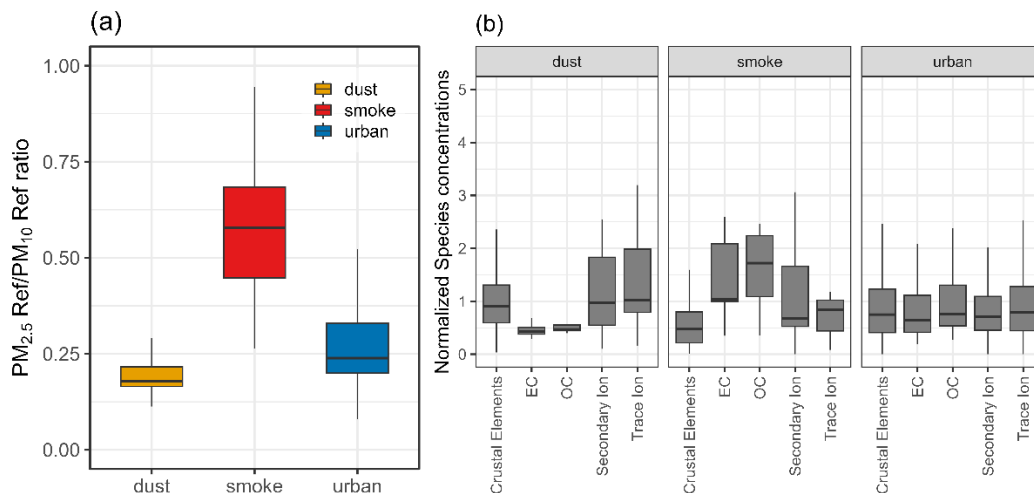



Figure 3. a) Daily averaged MOMA gain across the entire sensor network from July 2019 - April 2021. The daily values represent the mean of a 3-day rolling average applied to the hourly dataset, the shaded area is the standard deviation, b) relative humidity measured at the Phoenix Sky Harbor International Airport.

Given our findings, we separated our dataset into MOMA source categories representing 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 25 dust days (all in summer) and 16 smoke days (winter: 12, spring: 2, summer: 2) and 555 days dominated by typical urban conditions between July 2019 and April 2021. Figure 4 shows the mean reference PM$_{2.5}$/PM$_{10}$ ratio for each MOMA source category. As expected, smoke days were associated with a higher reference PM$_{2.5}$/PM$_{10}$ ratio (mean = 0.6) and with higher concentrations of elemental carbon (EC) and organic carbon (OC) compared to the other two categories which is also observed by Tong et al. (2012). Dust days, on the other hand, were dominated by larger particles (PM$_{10}$ = 13.7 − 126.4 µg m^{-3}, PM$_{2.5}$ = 3.7 − 18.4 µg m^{-3}) and higher concentrations of crustal elements compared to EC and OC concentrations. As a result, the PM$_{2.5}$/PM$_{10}$ ratio (mean = 0.2) was considerably lower compared to the smoke days. It is important to note that speciation data were only collected every third day and only nine out of the 25 sampling days contained a full complement of data. Other sampling days were missing some speciation data. The urban category showed a more uniform distribution of species concentrations. Some urban days may coincide with short-lived dust and smoke events, and applying the daily averaged MOMA gain across the entire network — along with the choice and representativeness of proxies and thresholds — introduces

258 classification uncertainties. The light grey shaded area in Figure 3a represents the standard deviation of the daily MOMA gain,
259 suggesting that the gain varies across sensors and hours within each day. This variability likely reflects differences in
260 environmental conditions and the sensor-reference relationship across the network. Nevertheless, the $PM_{2.5}/PM_{10}$ ratios are in
261 agreement with ratios (0.15 – 0.26) used by the U.S. EPA for fugitive dust particles (Midwest Research Institute (MRI), 2005)
262 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
263 Phoenix area).

264

265
266 **Figure 4. a) Daily averaged $PM_{2.5}/PM_{10}$ reference ratio measured across the AirNow reference network grouped by the**
267 **three MOMA source categories, and** **b) species concentrations, normalized to the mean category (Crustal Elements,**
268 **EC, OC, Secondary Ion, Trace Ion) values, measured at PJLG for the three different MOMA source categories.**

269

270 **3.2 Performance of MOMA under different conditions**

271 Figure 5 shows the co-located reference data against the PurpleAir data without any correction (a), with the EPA correction
272 (b), and the MOMA calibration against the nearest proxy reference (c) for data from the four co-location sites (Durango
273 Complex, West Phoenix, South Phoenix, Mesa – Brooks Reservoir). As previously observed (Barkjohn et al., 2021; Holder et
274 al., 2020; Jaffe et al., 2023), uncorrected PurpleAir sensor data correlated well with the co-located reference data as indicated
275 by the high R^2 (>0.7) for winter smoke and typical urban conditions but overestimated $PM_{2.5}$ at higher concentrations when
276 smoke particles are present and RH is high (mean bias error [MBE] = -7 µg m^{-3}). As expected, the relationship between the
277 PurpleAir sensors and the co-located reference is poorer during dust conditions (R^2 = 0.53) and the PurpleAir sensors
278 underestimated $PM_{2.5}$ (MBE = 3.1 µg m^{-3}). 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) and the MBE. Overall, MOMA performed comparably to the EPA correction in terms of MAE (2.8 – 3.7 µg m^{-3} for both) and root mean square error (RMSE) (4.8 – 6.2 µg m^{-3} vs. 4.5 – 7.6 µg m^{-3}, respectively) (Figure 5). MOMA performed slightly better correcting for dust conditions, but neither the EPA correction nor the drift calibration framework were able to fully correct for the missed dust particles at high concentrations and the RMSE remained high. This was also observed in Figure 6 which shows uncorrected, MOMA calibrated and EPA corrected data from August 2020 when a dust event (Figure 6a) moved over Phoenix followed by wildfire smoke (Figure 6b). Both the MOMA calibrated data and the EPA corrected data missed the dust spike but performed well during 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 the sensor during high wind, into its optical cavity, and/or poor light scattering design (Kuula et al., 2020; Ouimette et al., 2024). In fact, mean wind speeds were higher during dust days (mean = 3.5 m s^{-1}) compared to the other two MOMA source categories (< 3 m s^{-1}), supporting findings by Ouimette et al. (2024), who reported a decline in sampling efficiency for larger particles at wind speeds greater than 3 m s^{-1}. In contrast, during the wildfire episode (Figure 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., 2021; Jaffe et al., 2023) and has also been observed for the T640x (Barkjohn et al., 2022; Long et al., 2023).

Table 2 shows the number of days concentrations detected by the reference instrument were above the National Ambient Air Quality Standard (NAAQS) primary 24-hour PM$_{2.5}$ standard (35 µg m^{-3}) as measured by the uncorrected sensor data, the MOMA corrected data against the nearest proxy, and the EPA corrected data. The reference instruments did not report concentrations above this threshold under smoke or dust conditions but did so on seven days under typical urban conditions. Both the MOMA and EPA corrections improved accuracy near this concentration threshold but still slightly overestimated concentrations under urban conditions, with MOMA performing slightly better than the EPA correction.

301

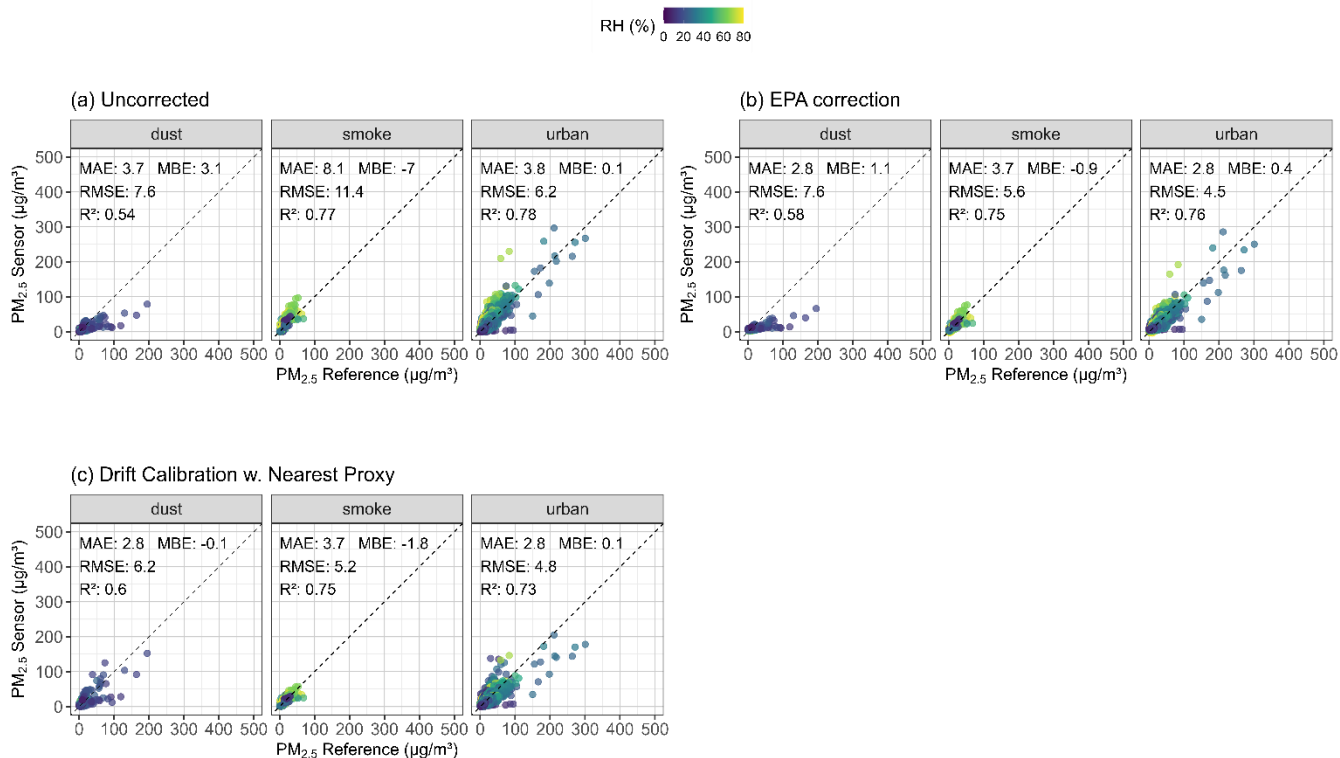



Figure 5. Hourly sensor measurements compared to reference data at the four co-location sites for a) uncorrected
('PM$_{2.5}$_atm') PM$_{2.5}$ sensor data, b) corrected sensor data using the EPA correction, and c) MOMA calibrated sensor
data using the nearest proxy reference across the MOMA source categories (Dust: 1992 hours, Smoke: 1251 hours,
Urban: 44601 hours). Points are colored by RH (%).

306

307

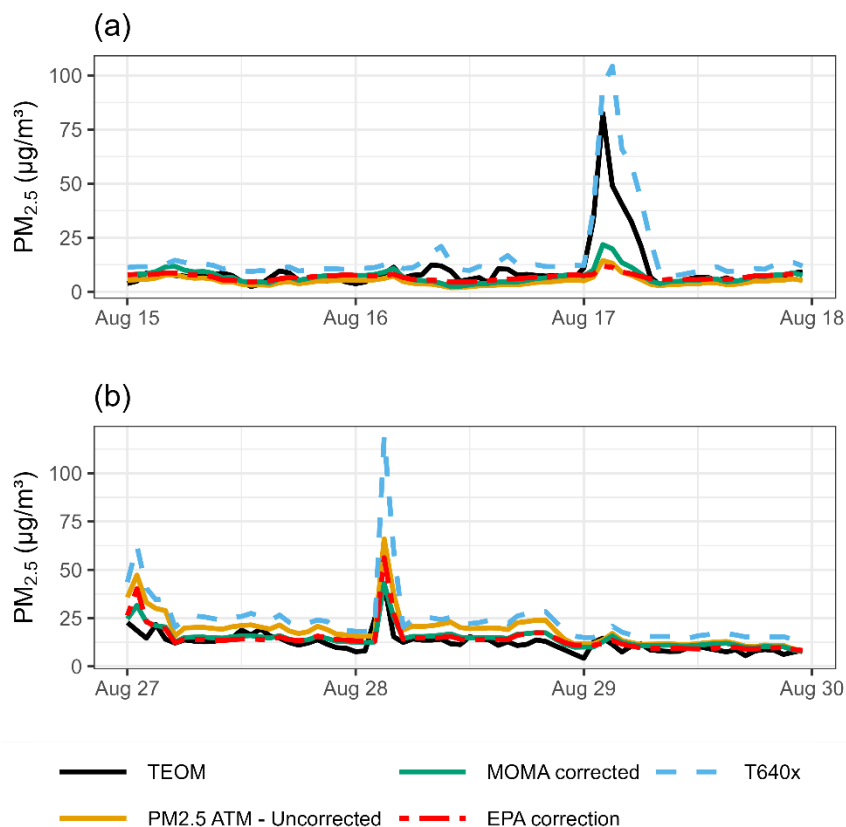



Figure 6. PM$_{2.5}$ concentrations measured at West Phoenix by the co-located TEOM and T640x reference and the

PurpleAir Sensor (PM2.5 ATM – Uncorrected), with the EPA correction and MOMA applied during the a) dust event,

and b) the wildfire smoke conditions.

311

Table 2. Number of times the daily average concentration went above the EPA primary 24-hour PM2.5 standard (> 35

µg m^{-3}) detected by the co-located PurpleAir sensors when using uncorrected, MOMA calibrated against the nearest

proxy, and the EPA corrected data across different MOMA source categories.

	PurpleAir Sensors			
MOMA source category	**Uncorrected**	**MOMA**	**EPA correction**	**Reference**
Dust	0	0	0	0
Smoke	5	0	0	0
Urban	42	12	14	7

315

316

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 MOMA source category 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, although there is some variation depending on the MOMA source category. This was observed across all sites however the improvement was slightly better at West Phoenix and Mesa – Brooks Reservoir. The sensor – proxy pair South Phoenix – Durango Complex does not appear to be a suitable match. Durango Complex is located next to the City of Phoenix Transfer Station, a garbage collection site, and the pollutant sources as well as temporal variations may therefore be different from those observed at South Phoenix, which is representative of a residential area. However, overall differences are small and the length of the window to trigger an alarm may also depend on the MOMA source category 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 PurpleAir sensors at the co-location sites West Phoenix, South Phoenix, Durango Complex and Mesa – Brooks Reservoir. Data were calibrated against the nearest proxy 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		
MOMA source category	**3 days**	**4 days**	**5 days**
Dust	-5	24	22
Smoke	59	54	58
Urban	24	26	26

4 Conclusions

This paper provided insights into the performance of the MOMA remote calibration tool and 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, MBE and RMSE as the EPA correction. The MOMA gain also provided a simple method of distinguishing between different MOMA source categories such as wood burning in winter and wildfires and dust events in summer. This may help identify PM sources based on sensor-reference

343 relationships. However, further analysis is required to test the application of this classification across other climate regions in

344 the U.S. or worldwide and to refine thresholds used to classify dust and smoke events and to distinguish these efficiently from

345 typical urban conditions.

346 We have highlighted the challenges in the calibration of PurpleAir sensors for Phoenix conditions in which the magnitude and

347 sources of $PM_{2.5}$ vary. The EPA correction is independent from reference sites and works well for smoke dominated conditions

348 but poorly for dust events. MOMA, being a dynamic method, is better at accommodating PM source variations but rapid,

349 short-term changes such as dust events and diurnally varying woodsmoke patterns can also be challenging. In addition, MOMA

350 is dependent on reliable proxy reference sites within 15 km to the sensor site representative of average pollution sources present

351 at the sensor site and the drift detection framework as applied here relies on several days of data to determine if a sensor has

352 drifted.

353

354 **Funding:** The measurement campaign was funded internally by the U.S. Environmental Protection Agency's Office of

355 Research and Development. In-kind field support was offered by Maricopa County Air Quality Department. In-kind analysis

356 support was offered by Aeroqual Ltd.

357

358 **Author contributions:** G.S.H., R.M.D. and A.L.C. formulated the overarching research goals and aims; A.L.C. planned and

359 implemented the field study; L.F.W. and G.S.H. developed the methodology for this analysis; C.C. organized and quality

360 assured the dataset used for this analysis; L.F.W. developed the software and performed the data analysis; L.F.W. prepared the

361 manuscripts with contributions from all co-authors; R.M.D., A.L.C. and G.S.H. supervised the project.

362

363 **Disclaimer**: This document has been reviewed in accordance with the U.S. Environmental Protection Agency policy and

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365 for use. The views expressed in this journal article are those of the authors and do not necessarily reflect the views or policies

366 or the U.S. Environmental Protection Agency.

367

368 **Competing interests:** The authors declare the following financial interests/personal relationships which may be considered as

369 potential competing interests: L.F.W. and G.S.H. are employees of Aeroqual Ltd, a sensor manufacturer. G.S.H. is a founder

370 and shareholder in Aeroqual Ltd.

371

372 **Code and Data availability:** The PurpleAir data from the Phoenix network are archived on Zenodo at

373 https://zenodo.org/records/15174476 (Clements et al., 2025). The dataset used to explore seasonal effects in the application of

374 the MOMA remote calibration tool is accessible via https://doi.org/10.23719/1532147 (Clements, n.d.). The code is not

375 publicly accessible due to intellectual property.

Acknowledgements: The authors acknowledge Sue Kimbrough (EPA retired), Ben Davis, Ron Pope, and Ira Domsky (Maricopa County Air Quality) for field study planning and implementation, Tim MacArthur, Alex Korff, Jacob Cansler, and Parik Deshmukh (Jacobs) for designing and building the P-TAQS pods, field data collection support by Robert Dyer (Maricopa County), data tracking and transfer by Nikki Petterson, Ceresa Steward, Hirna Patel (Maricopa County) and Brittany Thomas (Jacobs), and data quality assurance and preliminary data analysis by Ian VonWald (former ORISE postdoc to EPA).

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, Journal of Sensors, 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, Atmos. Meas. Tech., 14, 4617–4637, https://doi.org/10.5194/amt-14-4617-2021, 2021.

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? Environment International, 99, 293–302, https://doi.org/10.1016/j.envint.2016.12.007, 2017.

Clements, A., Kimbrough, E. S., VonWald, I., Croghan, C., Deshmukh, P., Davis, B., Pope, R., Domsky, I., and Dyer, R.: Phoenix-as-a-Testbed for Air Quality Sensors (P-TAQS) Dataset (v1). Zenodo. https://doi.org/10.5281/zenodo.15174476, 2025.

Clements, A. (n. d.). Phoenix-as-a-Testbed for Air Quality Sensors (P-TAQS) Dataset used in exploring the Seasonal Effects in the Application of the MOMA Remote Calibration Tool to Outdoor $PM_{2.5}$ Air Sensors [Data set]. U.S. EPA Office of Research and Development (ORD). https://doi.org/10.23719/1532147.

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, Environmental Modelling & Software, 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 Research, 24, 81–91, https://doi.org/10.1016/j.aeolia.2016.11.004, 2017.

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

410 English, P. B., Olmedo, L., Bejarano, E., Lugo, H., Murillo, E., Seto, E., Wong, M., King, G., Wilkie, A., Meltzer, D., Carvlin,
411 G., Jerrett, M., and Northcross, A.: The Imperial County Community Air Monitoring Network: A Model for Community-based
412 Environmental Monitoring for Public Health Action, Environ Health Perspect, 125, 074501, https://doi.org/10.1289/EHP1772,
413 2017.

414 Fann, N., Lamson, A. D., Anenberg, S. C., Wesson, K., Risley, D., and Hubbell, B. J.: Estimating the national public health
415 burden associated with exposure to ambient $PM_{2.5}$ and ozone., Risk Anal, 32, 81–95, https://doi.org/10.1111/j.1539-
416 6924.2011.01630.x, 2012.

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

420 Grineski, S., Bolin, B., and Boone, C.: Criteria Air Pollution and Marginalized Populations: Environmental Inequity in
421 Metropolitan Phoenix, Arizona n, Social Science Quarterly, 2007.

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

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

427 Jaffe, D. A., Miller, C., Thompson, K., Finley, B., Nelson, M., Ouimette, J., and Andrews, E.: An evaluation of the U.S. EPA's
428 correction equation for PurpleAir sensor data in smoke, dust, and wintertime urban pollution events, Atmos. Meas. Tech., 16,
429 1311–1322, https://doi.org/10.5194/amt-16-1311-2023, 2023.

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

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

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

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

442 Magi, B. I., Cupini, C., Francis, J., Green, M., and Hauser, C.: Evaluation of PM2.5 measured in an urban setting using a low-
443 cost optical particle counter and a Federal Equivalent Method Beta Attenuation Monitor, Aerosol Science and Technology,
444 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 Science and Technology, 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, Atmospheric Environment, 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?, Environment International, 116, 286–299, https://doi.org/10.1016/j.envint.2018.04.018, 2018.

Ouimette, J., Arnott, W. P., Laven, P., Whitwell, R., Radhakrishnan, N., Dhaniyala, S., Sandink, M., Tryner, J., and Volckens, J.: Fundamentals of low-cost aerosol sensor design and operation, Aerosol Science and Technology, 58, 1–15, https://doi.org/10.1080/02786826.2023.2285935, 2024.

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, Atmos. 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, Journal of the Air & Waste Management Association, 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 Pollution Research, 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, Environmental Pollution, 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.

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

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

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

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

490 U.S. EPA: Integrated Science Assessment for Particulate Matter (December 2019), U.S. Environmental Protection Agency,
491 Washington, DC, 2019.

492 Wallace, L., Bi, J., Ott, W. R., Sarnat, J., and Liu, Y.: Calibration of low-cost PurpleAir outdoor monitors using an improved
493 method of calculating PM$_{2.5}$, Atmospheric Environment, 256, 118432, https://doi.org/10.1016/j.atmosenv.2021.118432, 2021.

494 Wallace, L., Zhao, T., and Klepeis, N. E.: Calibration of PurpleAir PA-I and PA-II Monitors Using Daily Mean PM$_{2.5}$
495 Concentrations Measured in California, Washington, and Oregon from 2017 to 2021, Sensors, 22, 4741,
496 https://doi.org/10.3390/s22134741, 2022.

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

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

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

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

507

508