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Correction and Accuracy of PurpleAir PM_{2.5} Measurements for Extreme Wildfire Smoke

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Abstract: PurpleAir particulate matter (PM) sensors are increasingly used in the United States and other countries for real-time air quality information, particularly during wildfire smoke episodes. Uncorrected PurpleAir data can be biased and may exhibit a nonlinear response at extreme smoke concentrations (>300 µg/m³). This bias and nonlinearity result in a disagreement with the traditional ambient monitoring network, leading to the public's confusion during smoke episodes. These sensors must be evaluated during smoke-impacted times and then corrected for bias, to ensure that accurate data are reported. The nearby public PurpleAir sensor and monitor pairs were identified during the summer of 2020 and were used to supplement the data from collocated pairs to develop an extended U.S.-wide correction for high concentrations. We evaluated several correction schemes to identify an optimal correction, using the previously developed U.S.-wide correction, up to 300 µg/m³, transitioning to a quadratic fit above 400 µg/m³. The correction reduces the bias at each air quality index (AQI) breakpoint; most ambient collocations that were studied met the Environmental Protection Agency's (EPA) performance targets (twelve of the thirteen ambient sensors met the EPA's targets) and some smoke-impacted sites (5 out of 15 met the EPA's performance targets in terms of the 1-h averages). This correction can also be used to improve the comparability of PurpleAir sensor data with regulatory-grade monitors when they are collectively analyzed or shown together on public information websites; the methods developed in this paper can also be used to correct future air-sensor types. The PurpleAir network is already filling in spatial and temporal gaps in the regulatory monitoring network and providing valuable air-quality information during smoke episodes.

Keywords: air sensor; PurpleAir; PM_{2.5}; air quality index (AQI); correction; evaluation; wildfire smoke



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1. Introduction

Wildfires are one of the largest sources of the fine particulate matter (particles of 2.5 µm and smaller, PM_{2.5}) that is found in the atmosphere, contributing over 30% to the ambient PM_{2.5} concentrations across the U.S. [1] and severely degrading air quality in areas downwind from wildfire-prone regions [2]. The number of fires, the burned areas, and the duration of the fire season are increasing [3], leading to severe smoke impacts on air quality, as observed in California in 2020 [4,5]. Moreover, there was a reversal of long-term downward PM_{2.5} trends in the western United States, due to wildfire smoke [6]. Exposure to wildfire smoke has been linked to increased all-cause mortality and respiratory morbidity, with the very young, elderly, and individuals with respiratory disease being especially susceptible [7]. There are clear increases in adverse health outcomes being routinely observed, with increasing daily averaged PM_{2.5} concentrations of up to 200 µg/m³ [8]. However, smoke concentrations can be far higher, with some communities experiencing concentrations of above 800 µg/m³ for multiple hours over multiple days [9].

Additionally, wildland firefighters routinely work in areas with extremely high smoke concentrations, experiencing shift-average PM_4 (particulate matter with a median diameter of $4\ \mu m$) concentrations of approximately $500\ \mu g/m^3$ over an entire fire season [10].

In the United States, public health guidance to mitigate the impacts of smoke is based on the air quality index (AQI). The AQI is calculated from 24-h averages of $PM_{2.5}$ concentrations, corresponding to the evidence for $PM_{2.5}$ health impacts [11]. However, during wildfire smoke events, $PM_{2.5}$ concentrations can change rapidly, depending on the meteorology, the dynamics of the fire, and the local topography. Large increases or decreases in $PM_{2.5}$ concentration can be observed as the winds shift over the course of a day, setting up diurnal patterns of widely varying smoke concentrations. In the United States, the NowCast AQI was developed to address these dynamic conditions and is a weighted rolling average of hourly $PM_{2.5}$ concentrations [12].

In addition to public health guidance, air quality data are used for the occupational exposure of outdoor workers in California, Washington, and Oregon. Many of these regulations are at $PM_{2.5}$ AQI levels in the moderate to unhealthy for sensitive groups range (AQI = 69–201, $PM_{2.5}$ concentration = 20.5 – $150.5\ \mu g/m^3$). At these levels, the regulations require exposure controls (e.g., workers must move indoors or into vehicles with filtered air, move to an alternate location, or wear the respirators provided) [13–15]. In addition, the California Department of Industrial Relations (commonly known as Cal/OSHA) requires that once the $PM_{2.5}$ AQI exceeds 500 ($500\ \mu g/m^3$), the employer must provide and must expect employees to wear respirators [13]. Given these occupational thresholds for risk-reduction action, it is important to have accurate measurements up to $500\ \mu g/m^3$ to support occupational health decisions.

Large spatial gradients in $PM_{2.5}$ values can occur due to the localized smoke plumes and complex topography in the mountainous environment wherein many fires occur [2]. Therefore, the nearest regulatory or temporary monitoring site—sometimes 50–100 miles away—may not accurately represent the local smoke concentrations. Lower-cost air sensors can be used to fill in some of these gaps.

In order for air-sensor data to be actionable, sensors must be evaluated and, in some cases, corrected to provide accurate data over a wide range of concentrations and environmental conditions [16–18]. To evaluate and improve the performance of $PM_{2.5}$ air sensors, they are typically run alongside conventional $PM_{2.5}$ air monitors, in order to compare the reported concentrations [17,19,20]. It is important to evaluate the range of pollutant and environmental conditions that the sensors will be used to monitor as performance can be variable over different concentration ranges and can be influenced by environmental conditions, including relative humidity (RH) and temperature [21]. Sensor evaluations compared against air monitors are critical to gain actionable $PM_{2.5}$ data.

Over the past 5 years, the PurpleAir map has been increasingly used by the public, news media, and even some air quality agencies to fill in gaps in the monitoring network. Previous work has shown that PurpleAir $PM_{2.5}$ is highly correlated with the reference instruments, but it often reports higher values, in some cases by a factor of two, when compared to the reference measurements [17,22–28]. The PurpleAir response has shown some dependence on particle composition or size, with varying corrections needed for dust and light-absorbing aerosols [25,26,29]. However, a single correction factor has been shown to provide accurate $PM_{2.5}$ data (RMSE = $3\ \mu g/m^3$) across the United States, under a variety of aerosol types and environmental conditions [17]. The PurpleAir sensor exhibits a linear response to wildfire smoke at concentrations as high as $200\ \mu g/m^3$ [23,30]. Laboratory studies at higher concentrations of simulated smoke and other types of PM have shown that at elevated $PM_{2.5}$ concentrations, the PurpleAir has a quadratic or polynomial response up to $10\ mg/m^3$ [24]. This nonlinearity may be due to a variety of reasons, including sensor design and data-processing algorithms [21]. To our knowledge, there have yet to be any evaluations of PurpleAir sensors that account for nonlinearity above $200\ \mu g/m^3$ for wildfire smoke in the field.

With an appropriate correction, the PurpleAir sensor has the potential to provide accurate PM_{2.5} concentrations and greatly expand our knowledge of the air quality impacts of wildfire smoke. In August 2020, publicly available PurpleAir sensor data, with correction and quality checks, were displayed as a pilot effort, shown on the United States Environmental Protection Agency's (U.S. EPA) AirNow fire and smoke map (fire.airnow.gov). These sensors supplemented the relatively few PM_{2.5} monitors in the western United States, where most U.S. wildfires occur. As of January 2022, more than 12,000 PurpleAir sensors are shown on the fire and smoke map. Extreme smoke episodes over many parts of the western United States since 2020 have highlighted the need for more accurate PurpleAir data for very high concentrations of smoke (>200 µg/m³).

This study describes the development and evaluation of an extension to the U.S.-wide PurpleAir correction for high concentrations due to wildfire. We used the collocated and nearby sensor monitor pairs throughout the country during both typical ambient and smoke-impacted conditions to develop a correction between the PurpleAir-estimated PM_{2.5} and the monitor PM_{2.5}.

2. Materials and Methods

2.1. PurpleAir Sensors

The PurpleAir PA-II sensor is a lower-price (USD 230–260) PM sensor that is widely used globally, with many thousands of publicly reporting sensors. These sensors are purchased and deployed by individuals, community groups, government agencies, and others to better understand local air quality. The PurpleAir consists of two Plantower PMS5003 laser-scattering particle sensors, reporting PM₁, PM_{2.5}, PM₁₀, and particle counts in 6 bins from 0.3 to 10 µm. The two Plantower sensors within the device (channels A and B) sample at alternating 10-s intervals and provide 2-min-averaged data (80-s averaged data prior to 30 May 2019); this provides a redundant measurement of PM that can be used for quality control. The sensors also include a BOSCH BME280 sensor reporting temperature and relative humidity (RH). This temperature and RH sensor is positioned above the PM sensors inside the PVC cap, resulting in measurements that are strongly correlated with ambient temperature and RH but are somewhat warmer (2.7 to 5.3 °C) and dryer (9.7% to 24.3%) than ambient conditions [23,31,32]. A Wi-Fi-enabled chip allows the data to be uploaded to the cloud in near-real time. PurpleAir also makes a PA-II-SD model that saves the data to an SD card for applications where Wi-Fi is not available or for users who prefer to have a backup copy of the data in case the Wi-Fi drops out.

For this project, the 2-min or 80-s averaged data were downloaded for online sensors from the ThingSpeak API, using Microsoft PowerShell. These data were saved as .csv files that were then processed and analyzed in R [33] and Python. The offline sensor data were manually downloaded from the SD cards. The 2-min or 80-s data were averaged up to hourly data (where data that were collected between 08:00 and 08:59 became the 08:00 average). Hourly averages were excluded that did not contain at least 75% of the expected points (i.e., 33 points for 80-s averaged data, 22 points for 2-min averaged data) [34]. The 24-h averages were then computed from the 1-h averages from midnight to midnight. Those 24-h averages that were less than 75% complete (i.e., 18 h) were excluded.

The PM data reported by PurpleAir, at the time of publication, are identical to the Plantower PMS5003 output and are reported with two different labels. The [cf = 1] data are identical to the [cf = atm] data below roughly 25 µg/m³, as reported by the sensor, and then, the [cf = 1] transitions from 25–100 µg/m³ to reporting 50% higher values at concentrations above 100 µg/m³, compared to the [cf = atm] channel [17]. Some previous correction methods correct the [cf = 1] data [17,22,28,35], while others correct the [cf = atm] data [25]. These labels were switched (i.e., the [cf = atm] label on the higher data column, now labeled [cf = 1]) by PurpleAir until late 2019, leading to some confusion and discrepancies in the older literature [31]. We used the [cf = 1] data in this paper since we, and others, have previously shown that it is more strongly correlated to reference monitors over the full range of concentrations [17,28].

A quality control procedure was applied to the hourly data to remove potentially spurious readings. The hourly data were considered valid if the difference between the A and B channel PurpleAir PM_{2.5} values were within 5 µg/m³, or the relative percentage difference was less than 70%, resulting in 2.7% of the hourly averages being removed. The percentage criterion was relaxed from the 62% thresholds used in previous analyses of 24-h averaged data [17], due to the sensor having higher noise levels at hourly averages.

2.2. Monitors

For this project, twenty-five sensors collocated or near-collocated with the monitors were identified across the U.S. These sites span eight or nine continental U.S. climate regions [36,37], with most of the smoke-impacted sites being located in the west and northwest.

2.2.1. Collocated Monitoring in Typical Ambient Conditions

Many ambient sensors were part of the U.S. EPA's long-term performance project (LTPP); PurpleAir sensors were collocated at the regulatory monitoring sites in: Research Triangle Park, NC; Wilmington, DE; Decatur, GA; Edmond, OK; Denver, CO; Phoenix, AZ; Missoula, MT; and Sarasota, FL, beginning around July 2019. Additionally, a few collocated sensors operated by local air-monitoring agencies in Appleton, WI, Atascadero, CA, Cedar Rapids, IA, Marysville, WA, and Topeka, KS were used (Table 1). These sites represent a variety of climates and experience variations in particle concentration, composition, and size. These data are representative of typical ambient conditions, as observed across much of the United States.

Table 1. Ambient summary of the hourly averaged typical ambient dataset locations, comparison monitor types, date ranges, and the number of data points (N). T640 and T640x data over 35 µg/m³ are excluded from this table and the analysis in the paper. All ambient sensors were collocated by the EPA or a partner.

Location	Monitor Type	Date Range	N
Appleton, WI	BAM-1020	01/01/2019–24/01/2019	574
	T640	25/01/2019–09/01/2020	8171
Atascadero, CA	BAM-1020	01/01/2018–24/10/2019	15,108
Cedar Rapids, IA	BAM-1020	05/05/2018–08/10/2020	27,456
	T640	04/09/2019–06/08/2020	232
Decatur, GA	T640x	01/08/2019–31/08/2020	6868
Denver, CO	T640	14/08/2019–30/09/2020	8828
Edmond, OK	T640	02/08/2019–31/12/2019	3130
	T640x	03/01/2020–30/09/2020	5044
Marysville, WA	BAM1020	01/01/2019–31/08/2020	8900
	1405-F	25/10/2018–31/12/2018	1616
Missoula, MT *	BAM-1020	22/11/2019–28/07/2020	1738
Phoenix, AZ	TEOM	28/10/2019–31/07/2020	3652
RTP, NC *	T640x	01/08/2019–19/11/2019	1921
Sarasota, FL	T640	30/05/2019–30/06/2020	9145
Topeka, KS	T640	12/03/2019–30/06/2020	8288
Wilmington, DE	T640	27/07/2019–30/06/2020	5705
All Ambient	13 sensors ***	01/01/2018–08/10/2020	116,376
All Smoke and Ambient sites **	27 sensors	01/01/2018–20/10/2020	134,458

* A different sensor from that deployed during the smoke impact tests. ** Includes all the ambient sensors listed in this table and all the smoke sensors listed in Table 2. *** 13 sensors paired with 17 monitors as some sites ran multiple monitors simultaneously or switched monitor types during the collocation.

2.2.2. Collocated Monitoring in Smoke-Impacted Conditions

The smoke-impacted datasets were collocations of the PurpleAir sensors at ambient monitoring sites that were impacted by wildfire smoke and at temporary smoke-monitoring installations near prescribed fires or wildfires (Table 2 and Table S1 in the Supplementary Materials). A short-term collocation in Pinehurst, CA with a Met One BAM 1020, a federal-equivalent method (FEM) device, recorded elevated concentrations due to prescribed fire

and aged wildfire smoke during October 2018. A long-term collocation with a Grimm EDM-180 (FEM) at the U.S. EPA's Ambient Air Innovation Research Site (AIRS) in Research Triangle Park, North Carolina was impacted by the smoke from multiple prescribed fires. A long-term collocation with a BAM 1020 (FEM) in Missoula, Montana was impacted by a prescribed fire and smoke event. Two other smoke-impacted datasets were derived from temporary deployments located near fires. The temporary deployments were carried out near the 2018 Natchez wildfire in Happy Camp, CA, collocated with a Met One E-BAM (non-FEM) and a 2019 prescribed fire/pile burn near Oakley, UT, collocated with a Met One E-Sampler (non-FEM).

Table 2. Smoke-impact summary of the hourly averaged smoke-impacted dataset locations, monitor types, fires, date ranges, number of data points (N), concentration, and RH range. All PurpleAir sensors have >99% of the RH data present. Some sensors were collocated, while others were nearby sensor monitor pairs identified on the fire and smoke map. Most datasets are 2–3 months long, including both the smoke-impacted time and some typical ambient conditions.

Nearby or Collocation	Location	Monitor Type	Fire	Date Range	N
Smoke nearby identified on fire and smoke map	Bend, OR	M903 Nephelometry	Beachie Creek wildfire	01/08/2020–19/10/2020	1758
	Boise, ID	BAM-1020	Aged OR smoke	01/08/2020–20/10/2020	1753
	El Portal, CA	E-BAM	Creek Fire	20/08/2020–19/10/2020	1279
	Forks of Salmon, CA	E-BAM	Red Salmon Complex wildfire	14/08/2020–20/10/2020	1199
	Hoopa, CA	E-BAM	Red Salmon Complex wildfire	31/07/2020–20/10/2020	1632
	Keeler, CA	TEOM	Creek wildfire	01/08/2020–20/10/2020	1876
	Oakridge, OR	BAM-1022	Archie Creek wildfire	01/08/2020–19/10/2020	1865
	Oroville, CA	E-BAM	North Complex wildfire	26/08/2020–15/10/2020	1016
	Tulelake, CA	E-BAM	Red Salmon Complex and Slater wildfires	31/07/2020–20/10/2020	1720
	Smoke collocated by EPA or partner	Atascadero, CA	BAM-1020	River—Dolan wildfire and ambient	01/08/2020–19/10/2020
Happy Camp, CA		E-BAM	Natchez wildfire	11/08/2018–29/08/2018	348
Missoula, MT *		BAM-1020	Prescribed	18/07/2019–12/09/2019	1152
Oakley, UT		E-Sampler	Prescribed	01/11/2019–04/11/2019	48
Pinehurst, CA		BAM1020	Prescribed fire and aged wildfire smoke	20/10/2018–27/10/2018	157
RTP, NC *		Grimm	Prescribed	13/03/2019–31/03/2019	429
All Smoke	15 sensors			11/08/2018–20/10/2020	18,082

* This is a different sensor from the sensor deployed during ambient testing.

2.2.3. Nearby Sensor Monitor Pairs Identified on the AirNow Fire and Smoke Map

In addition to the true collocations performed as part of the U.S. EPA's research projects, we identified sites with sensors located close to temporary or permanent monitors on the AirNow Fire and Smoke Map that were impacted by smoke from wildfires during the period of August to October 2020. Sites were selected that experienced smoke concentrations above $250 \mu\text{g}/\text{m}^3$, as measured by the monitor, as well as in other geographic locations with lower concentrations and less data collected (e.g., Boise, ID) (Table 2). All sites were within roughly 3 km of the nearest monitor (although many were closer) to minimize the impact of spatial and temporal variations in smoke concentrations on the comparison between the sensor and the monitor (Table S2 in the Supplementary Materials).

2.2.4. Air Monitoring Equipment and Data Access

PM_{2.5} Monitors: Permanent Federal Equivalent Method (FEM) and Temporary Smoke Monitors

Permanent monitors were installed at stationary monitoring sites as part of federal or state regulatory networks, using a variety of measurement technologies and instrumentation. Most permanent monitors have an FEM designation [38,39] that is suitable for the regulatory monitoring of PM_{2.5} via 24-h averages. FEM monitors used in collocations for this study included light-scattering-based PM_{2.5} detection methods, including the T640 or T640x (Teledyne API, San Diego, CA, USA) and the EDM-180 (GRIMM Aerosol Technik, Ainring, Germany), beta-attenuation-based PM_{2.5} measurements (MetOne BAM 1020 or BAM 1022, Met One Instruments, Grants Pass, OR, USA), and tapered-element oscillating microbalance-based PM_{2.5} measurements (TEOM 1405, Thermo Fisher Scientific, Waltham, MA, USA). Nephelometer-based (Radiance Research, Seattle, WA, USA) permanent monitors without a FEM designation were also used in this study since they report to AirNow and typically offer adequate performance [40–42].

Temporary deployments of non-FEM, portable PM_{2.5} instruments are employed in areas prone to wildfires and where permanent monitors are sparse. The MetOne E-BAM and E-Sampler are the most common monitors used in these temporary deployments. Although these instruments do not have a FEM designation, they do have quality control procedures (e.g., zero checks, leak checks, and flow audits) and have been evaluated with smoke, both in the laboratory [26,43,44] and in the field [45], and provide accurate PM_{2.5} smoke concentrations up to 1500 µg/m³.

Data from the permanent and temporary monitors were obtained using multiple different methods. Temporary monitor data were obtained through a direct data download from the instrument, via the Interagency Wildland Fire Air Quality Response Program (IWFAQRP) Monitoring 4.1 website (<https://tools.airfire.org/monitoring/v4>, accessed on 19 August 2021), and through the Airsis web-based instrument download (<https://app.airsis.com/USFS/>, accessed on 3 January 2022). The IWFAQRP data are quality controlled to remove data where the internal relative humidity is greater than 40%, the instrument flow rate is outside the range of 15.7–16.7 lpm, with negative PM_{2.5} concentrations set to zero. Any additional clear outliers were removed from the reference datasets (Figure S1 in the Supplementary Materials). The direct instrument downloads do not have any quality-control procedures applied. Permanent data were downloaded from the U.S. EPA's Air Quality System (AQS) and have been quality-controlled by local agencies.

Quality Assurance of Permanent Monitors

The accuracy of the permanent monitors was evaluated using the PM_{2.5} continuous monitor comparability assessment tool, which allows the automatic plotting of the FEM data against the collocated federal reference method (FRM) filter data (<https://www.epa.gov/outdoor-air-quality-data/pm25-continuous-monitor-comparability-assessments>, accessed on 7 July 2022). Sixteen out of twenty-two monitors had comparability assessments; of these, eight of the sixteen monitors had slopes outside the target range (1 ± 0.1) (Tables S3 and S4 in the Supplementary Materials). Many of these devices were Teledyne T640s and T640xs. T640s and T640x are optically based FEMs that may have less noise at low concentrations but may have nonlinear bias compared to other PM_{2.5} measurement methods [46] (Figure S2 in the Supplementary Materials). Because of the nonlinear performance at high concentrations, T640 and T640x data above 35 µg/m³ was excluded and no T640 or T640x monitors were used as reference measurements during smoke events (see additional details in Section S3 of the Supplementary and Tables S5 and S6 of the Supplementary Materials). Data were used from T640 and T640x collocations at typical ambient sites up to 35 µg/m³ to build and evaluate the correction; these provide valuable data with low noise at low concentrations across more parts of the country than would have been represented if no T640 or T640x data were included.

2.3. Correction Development

Most corrections for PurpleAir sensors do not account for the nonlinearity seen under extreme concentrations (Figure 1). We considered several corrections, including terms to account for RH (Table 3) since previous studies have suggested that humidity levels can impact the relationship between PurpleAir (or Plantower) and the monitor PM_{2.5} values [32,47–49]. Many of the equations considered in this paper include interaction terms (i.e., PM × RH) because RH and PM_{2.5} are slightly (but often significantly) correlated. We also considered a nonlinear impact of RH that was similar to that used in previous work [28].

2.3.1. Withholding

To ensure that the selected correction models were not overfitted, we built and tested each model by withholding a portion of the dataset for evaluation only. We first built each model in Table 3 using all but one sensor and then tested it on the excluded sensor (“leave one sensor out”). This resulted in 27 iterations of each model type, with datasets

from each sensor. Each sensor had a variable range of $PM_{2.5}$ concentrations, but only five sensors reported data with concentrations above $500 \mu\text{g}/\text{m}^3$. The sensors also experienced a range of RH (0–100%), with some having typically low RH (e.g., the Phoenix mean has an RH = 18%), some having typically high RH (e.g., the Marysville mean has an RH = 74%), and some a broad range (e.g., the Topeka mean = 50%, range = 10–80%). The datasets also covered a wide range of times, with some sites representing longer time periods than others (Figure 2). We also withheld according to the week of the year, building on all but one week of the year (“leave one week out”), and then testing on that week. Many weeks had data from 3 years (i.e., 2018, 2019, or 2020) (see Figure S3 in the Supplementary Materials). Most weeks had a wide range of RH conditions, while multiple weeks had high concentrations from smoke impacts.

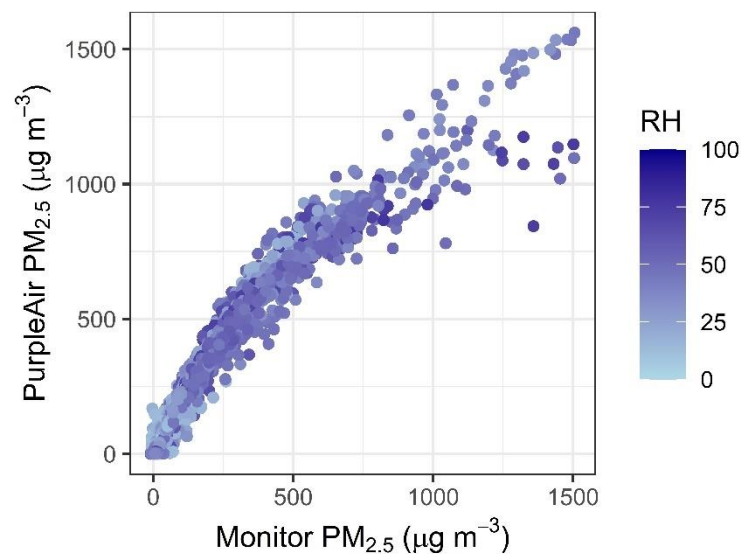


Figure 1. Nonlinearity in hourly PurpleAir $PM_{2.5}$, uncorrected [cf = 1], versus the monitor $PM_{2.5}$ values, colored by the relative humidity, as measured by the PurpleAir.

Table 3. Correction equations that were considered.

Model	Fit	Equation
A	U.S. correction	$PM_{2.5} = 0.524 \times PA_{cf,1} - 0.0862 \times RH + 5.75$
B	Quadratic	$PM_{2.5} = a \times PA_{cf,1}^2 + b \times PA_{cf,1} + c$
C	Cubic	$PM_{2.5} = a \times PA_{cf,1}^3 + b \times PA_{cf,1}^2 + c \times PA_{cf,1} + d$
D	Quadratic + RH	$PM_{2.5} = a \times PA_{cf,1}^2 + b \times PA_{cf,1} + c + d \times RH$
E	Quadratic PM * RH	$PM_{2.5} = a \times PA_{cf,1}^2 + b \times PA_{cf,1} + c + d \times RH + e \times PA_{cf,1} \times RH$
F	RH growth, Nilson [28]	$PA_{cf,1}/\text{monitor} = a + \frac{b}{\left(\frac{100}{RH} - 1\right)}$ (RH limited 30–70%)

2.3.2. Correction Selection

We then evaluated the models by normalized mean bias error (NMBE) and simplicity. Simplicity was defined as the number of terms in the equation, with a linear model more simple than a quadratic model, a quadratic model more simple than a cubic model, and an RH term, increasing the complexity of each model type. If two models performed adequately, the simpler of the two models would be selected. We wanted to select a model that would keep the normalized mean bias error within 10% at each AQI breakpoint and at the threshold of $500 \mu\text{g}/\text{m}^3$, using a piecewise model, if needed, and employing the simplest model that would meet this requirement. We evaluated the performance at each AQI breakpoint (Table S7 in the Supplementary Materials) according to public health guidance changes at each level (e.g., limiting outdoor activity); therefore, this is where sensor accuracy is most important. We also evaluated the performance at $500 \mu\text{g}/\text{m}^3$, which is the Cal/OSHA level at which a respirator should be worn. We evaluated the

NMBE at each breakpoint, using bins of data within $\pm 20\%$ around each breakpoint, to ensure an adequate number of hourly measurements in each bin. We also included bins for concentrations below and above the breakpoints to ensure results outside our targeted range were not unreasonable.

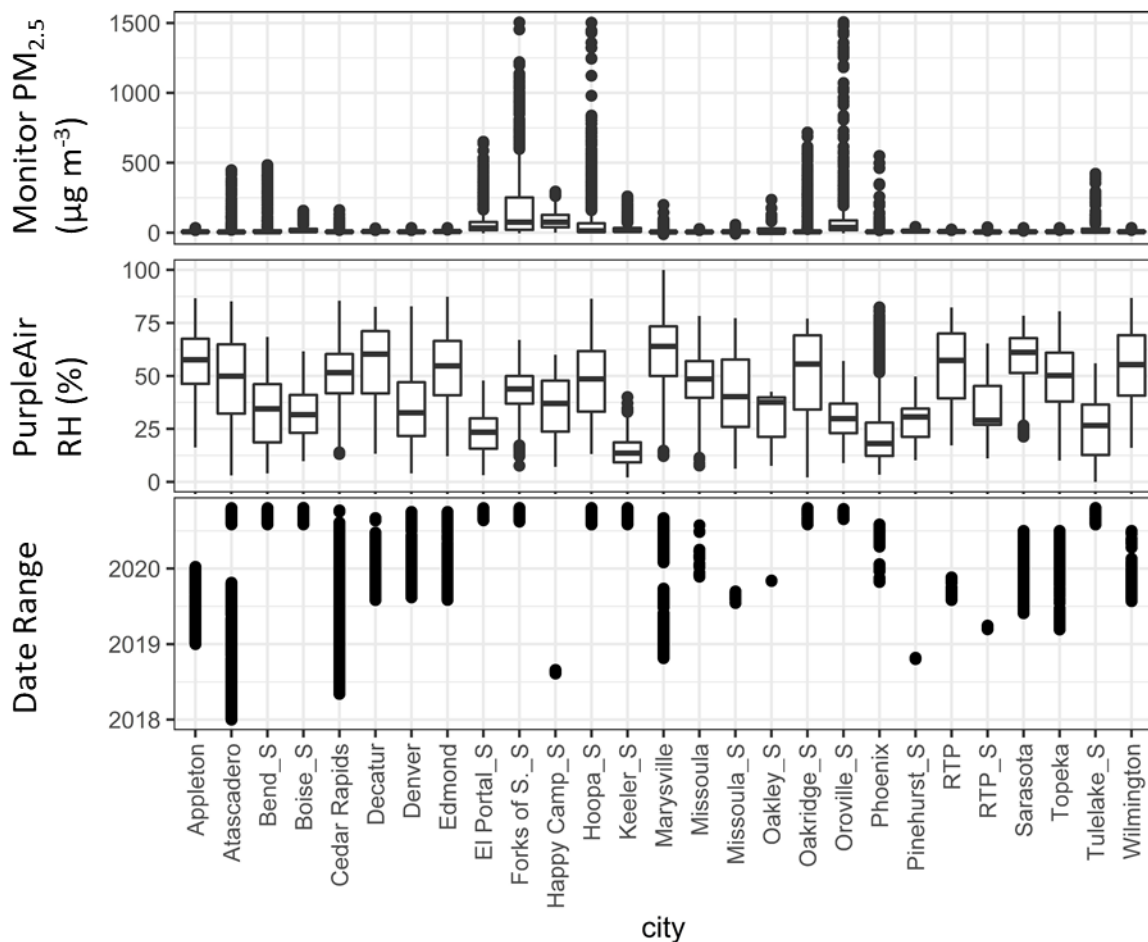


Figure 2. Summary of the distribution of RH and $PM_{2.5}$ for each sensor (withholding groups). The Atascadero sensor experienced both typical ambient and smoke-impacted periods.

2.4. Correction Evaluation

After a correction was selected, the corrected dataset (generated using withholding) was evaluated at hourly, 24-h, and NowCast averages using the recommendations from the EPA air sensor performance target report for $PM_{2.5}$ [50]. The report recommends procedures for evaluating sensors in field and lab environments and specifies metrics including the ordinary least squared regression slope, intercept, R^2 , root mean squared error (RMSE), and normalized root mean squared error (NRMSE), along with target thresholds. To meet the targets, the sensor must meet either the RMSE target or the NRMSE target; the NRMSE is typically used for high concentrations (e.g., smoke events), where larger absolute (RMSE) errors are common. Although the report recommends that sensors be evaluated at 24-h averages, the same criteria can also be used on 1-h averages.

We also evaluated how often the corrected PurpleAir data reported the same NowCast AQI category as the monitor. The NowCast is a 12-h weighted average that is weighted based on the variability of concentrations (see details on the NowCast in the Supplementary Materials, Section S4). To convert the concentration into AQI, the U.S. EPA's AQS reference table was used [51] (see Table S7 in the Supplementary Materials). Evaluating performance in both hourly and NowCast averages provides a better understanding of the accuracy of the data displayed on the fire and smoke map, which currently displays NowCast, hourly

averages, and 10-min-averaged sensor data. The evaluation of 24-h averages allows us to better compare the corrected PurpleAir measurements to the performance targets and removes some of the uncertainty in the 1-h monitor measurements.

3. Results and Discussion

3.1. Selecting an Equation

3.1.1. Collinearity of Terms

Many of the equations considered in this paper include the interaction terms (i.e., $PM \times RH$) because RH and $PM_{2.5}$ are slightly (but often significantly) correlated (PurpleAir [cf = 1] $PM_{2.5}$ with PurpleAir RH $R^2 = 0.002$, with collinearity of $p < 2.2 \times 10^{-16}$, Monitor $PM_{2.5}$ with PurpleAir RH $R^2 = 0.003$, $p < 2.2 \times 10^{-16}$). However, this requires a wider range of combinations of RH and $PM_{2.5}$ (e.g., a high RH and high $PM_{2.5}$, a high RH and low $PM_{2.5}$, a low RH and low $PM_{2.5}$, and a low RH and high $PM_{2.5}$).

3.1.2. Best Equation, Based on NMBE and Simplicity

The optimal equations were selected based on the NMBE at each breakpoint (Tables S8 and S9 in the Supplementary Materials). No single proposed equation kept the NMBE at $\leq 10\%$ across all breakpoints. The U.S.-wide correction equation was the best-fitting model for $PM_{2.5}$ concentrations $< 10 \mu\text{g}/\text{m}^3$; the NMBE is $\leq 10\%$, up to (and including) the breakpoint to the classification of “Hazardous” ($250.4 \mu\text{g}/\text{m}^3$). At the Cal/OSHA limit, the U.S.-wide correction leads to an NMBE $> 10\%$, and the quadratic fit is the simplest fit that keeps the NMBE at $\leq 10\%$. The results are similar whether using week or site withholding. Using a piecewise equation that includes both the U.S.-wide correction and the quadratic fit at higher concentrations meets the criteria of NMBE $\leq 10\%$ at each breakpoint of interest (see Table 4).

Table 4. The 1-h error at each AQI breakpoint, using site withholding and a transition from the U.S.-wide correction to a quadratic fit from 300 to 400 $\mu\text{g}/\text{m}^3$ (raw [cf = 1] 570–611 $\mu\text{g}/\text{m}^3$).

AQI Breakpoint	Concentration Range ($\mu\text{g}/\text{m}^3$)	N	Selected Fit	NMBE	RMSE ($\mu\text{g}/\text{m}^3$)	NRMSE
Below	0–10	90,960	U.S.-wide	−5%	3	54%
Moderate	10–14	15,205	U.S.-wide	−10%	4	31%
UHSB	28–42	2196	U.S.-wide	4%	9	27%
Unhealthy	44–66	1291	U.S.-wide	9%	12	22%
Very Unhealthy	120–180	503	U.S.-wide	2%	18	12%
Hazardous	200–300	475	U.S.-wide	−5%	31	12%
Cal/OSHA	400–600	230	Quadratic	0%	89	18%
Beyond	600+	189	Quadratic	−7%	216	25%

3.1.3. Final Equations

The U.S.-wide equation reduced the NMBE to $\leq 10\%$, up to the breakpoint to “Hazardous”, and the quadratic fit is the best and simplest fit around the Cal/OSHA respirator limit, based on the NMBE (best fit) and the number of terms (simplicity). Since the transition falls in the “Hazardous” category, we transitioned from roughly 300–400 $\mu\text{g}/\text{m}^3$, corrected so that the transition zone does not impact data near either the “Hazardous” breakpoint or the Cal/OSHA respirator limit, keeping the error low throughout the transition (Table S10 in the Supplementary Materials). We transitioned linearly from using 100% of Equation (1) (model A, the original U.S.-wide correction) to 100% of Equation (3) (model B, with a quadratic fit), as shown in Equation (2) (Figure S4 in the Supplementary Materials). The transition zone was selected by calculating the raw PurpleAir [cf = 1] (PA_{cf1}) value that would result from a corrected $PM_{2.5}$ concentration of 300 $\mu\text{g}/\text{m}^3$, using the U.S.-wide correction at 50% RH and 400 $\mu\text{g}/\text{m}^3$, employing the quadratic fit:

$$\begin{aligned} PA_{cf1} < 570 \text{ (corrected} &= 300 \mu\text{g}/\text{m}^3 \text{ at 50\% RH)} \\ PM_{2.5} &= PA_{cf1} \times 0.524 - 0.0862 \times RH + 5.75 \end{aligned} \quad (1)$$

$$570 \leq PA_{cf1} < 611$$

$$PM_{2.5} = (0.0244 \times PA_{cf1} - 13.9) \times [\text{Equation (3)}] + (1 - (0.0244 \times PA_{cf1} - 13.9)) \times [\text{Equation (1)}] \quad (2)$$

$$PA_{cf1} \geq 611 \text{ (corrected } 400 \mu\text{g}/\text{m}^3\text{)}$$

$$PM_{2.5} = PA_{cf1}^2 \times 4.21 \times 10^{-4} + PA_{cf1} \times 0.392 + 3.44 \quad (3)$$

In the equations, RH represents the relative humidity, as measured by the PurpleAir. The transition is needed to reduce the gap between equations. Simplicity is prioritized to reduce the computation time, which precludes the use of a sigmoid transition (i.e., a mathematical function with an S-shaped curve). We considered merging the datasets at the intersection between the two curves at 50% RH. However, since only the linear correction includes RH, this would lead to a discontinuity of up to $4 \mu\text{g}/\text{m}^3$ at high and low RH. For example, if the concentration rose by $1 \mu\text{g}/\text{m}^3$ at the transition point between equations, the estimated $PM_{2.5}$ could fall by $4 \mu\text{g}/\text{m}^3$ if the RH was 0%. Therefore, the transition is effective in tapering the influence of the RH term. The transition is not essential; therefore, for applications that prioritize simplicity, Equation 1 can be used for concentrations up to $300 \mu\text{g}/\text{m}^3$, while Equation (3) can be used for concentrations of $300 \mu\text{g}/\text{m}^3$ and above.

3.1.4. Discussion Influence of RH

As reported in our previous work [17], here, we do not see exponential increases in $PM_{2.5}$ estimates at high humidity (>60–80% RH). Although the hygroscopic growth of particles can lead to exponential light scattering [52], it does not appear to impact the PurpleAir data used in this study, which is potentially due to the sensors keeping the particles slightly warmer or dryer, or is due to some particles growing to a size that is not easily detected by the PurpleAir [53]. The additive RH term is still effective at correcting and improving the sensor accuracy from 0 to $300 \mu\text{g}/\text{m}^3$.

It is unclear what the influence of RH may be on PurpleAir performance at high concentrations. Over $\sim 750 \mu\text{g}/\text{m}^3$, the higher RH appears to lead to lower $PM_{2.5}$ estimates from the PurpleAir sensors (Figure 1). However, this data is from only three sensors (Forks of Salmon, Hoopa, and Oroville, Figures S5 and S6 in the Supplementary Materials). The RH range experienced at each of these sites during these high concentration times is quite limited (range < 24%), making it unclear whether this apparent RH influence is due to the difference in monitor sensor agreement at the 3 sites or is due to higher RH values, leading to sensor saturation at lower concentrations. Additional data would be needed to better understand the influence of RH at high $PM_{2.5}$ concentrations; however, monitors may also demonstrate large uncertainties at these extreme conditions, which may lead to further challenges in quantifying this relationship.

3.2. Evaluation of the Correction—EPA Performance Target Evaluation at 1-h and 24-h Averages

Both the withholding methods resulted in similar sensor performance. The ambient sensors performed well, meeting or very nearly meeting the targets at both 1-h and 24-h averages (see details in SI Section S6), with slopes within 1 ± 0.31 , intercepts within $\pm 2 \mu\text{g}/\text{m}^3$, RMSE $\leq 6 \mu\text{g}/\text{m}^3$, and $R^2 \geq 0.66$ (target $R^2 \geq 0.70$). Smoke-impacted sensors typically met or were near to the 24-h averaged targets with slopes within 1 ± 0.38 (target 1 ± 0.35), intercepts within $\pm 13 \mu\text{g}/\text{m}^3$ (target $\pm 5 \mu\text{g}/\text{m}^3$), NRMSE $\leq 40\%$ (target $\leq 30\%$), and $R^2 \geq 0.61$ (target $R^2 \geq 0.70$). At the 1-h averages, the smoke-impacted sensors still typically met or nearly met the targets, although in some cases, this was with larger errors (NRMSE of up to 55%). While not all the sensors evaluated met the performance targets, it is important to note that the performance targets are not pass/fail certifications but are instead a recommendation to encourage overall performance improvement of the technology entering the market. Falling short of these targets does not mean that the data are unusable.

It is also important to note that not all recommendations in the performance targets were followed in this evaluation. Many of the smoke-impacted sites were selected as nearby

monitor sensor pairs on the fire and smoke map and, therefore, may not be true collocations. Some of the scatter (RMSE) in the comparisons may be due to real concentration differences. In addition, the performance targets report recommends evaluating the sensors in triplicate. Here, we have evaluated a single sensor at each site. However, past work with PurpleAir sensors has already established their high precision (especially when using the duplicate Plantower sensors for quality control) and so this may be less of an issue for this sensor type [17,20,31,54]. Lastly, not all sensors were evaluated against FEMs, as recommended in the performance targets document [50]. However, this recommendation is less relevant for smoke monitoring, wherein FEMs also show uncertainty since their designation involves field-testing at typical ambient, not smoke-impacted, conditions.

3.3. Negative Values at Hourly Averages

Monitoring sites typically retain negatives that are near zero to represent the baseline noise of the instrument. After correction using withholding, 1.5% of the PurpleAir data were negative, compared to 1.9% of the monitor data. The lower percentage of negatives from the PurpleAir sensors versus the monitors suggests that the PurpleAir sensors are not reporting an unreasonable number of negative values. On the AirNow fire and smoke map, all the negative values that are displayed are rounded to zero; however, in this work, negative values have been retained for the purposes of analysis.

3.4. NowCast Averaged Performance

Overall, the corrected data predicted the NowCast AQI category correctly for 94% of the time (Figure 3 and Table S15 in the Supplementary Materials). When the PurpleAir and monitor reported different AQI categories, often (77% of the time), the concentrations reported were within $5 \mu\text{g}/\text{m}^3$ (e.g., the PurpleAir concentration is $10 \mu\text{g}/\text{m}^3$ and the monitor concentration is $13 \mu\text{g}/\text{m}^3$, leading to different AQI categories but with only a concentration difference of $3 \mu\text{g}/\text{m}^3$). In all categories, <1% of the points are of more than one category different.

The “Hazardous” category has the highest percentage of points that underestimate the AQI category (12%). There is a slight underestimation at the breakpoint between “Very unhealthy” and “Hazardous” (NMBE = -5%); however, much of this underestimation is due to the large variability in agreement between the PurpleAir and the monitors at these high concentrations (see the scatter plot in Figure 1). This is also reflected in the increasing RMSE at the breakpoint between “Very unhealthy” and “Hazardous” (RMSE = $31 \mu\text{g}/\text{m}^3$). It is also important to note the more limited number of values in the hazardous AQI category (N = 969, 0.6% of the full dataset), meaning that these results may be less representative of a larger sample size. Additional hazardous AQI category data could enable better-tuned correction in the future.

3.5. Comparisons to Other Published Corrections

At concentrations of up to $300 \mu\text{g}/\text{m}^3$, the extended U.S.-wide correction is consistent with other corrections that are currently in use on the PurpleAir map (ALT cf = 3, Woodsmoke, AQandU, LRAPA, map.purpleair.com, accessed on 26 July 2022) (Figure 4). However, all other corrections that are in use on the PurpleAir map significantly underestimate the values at high concentrations ($>300 \mu\text{g}/\text{m}^3$) (the Nilson equation is not an option on the PurpleAir map and is discussed in the next paragraph). The ALT [cf = 3] correction [55] may improve performance near the limit of detection, but it does not lead to improved performance in other concentration ranges. Moreover, the ALT [cf = 3] correction is impractical, requiring more data fields and additional calculations, which increases the computational requirements for large-scale mapping, as used in the AirNow fire and smoke map or other such applications. However, better quantification near the limit of detection may be more important for sensors that are used in very clean environments (e.g., indoors) and when seeking to calculate more accurate long-term trends.

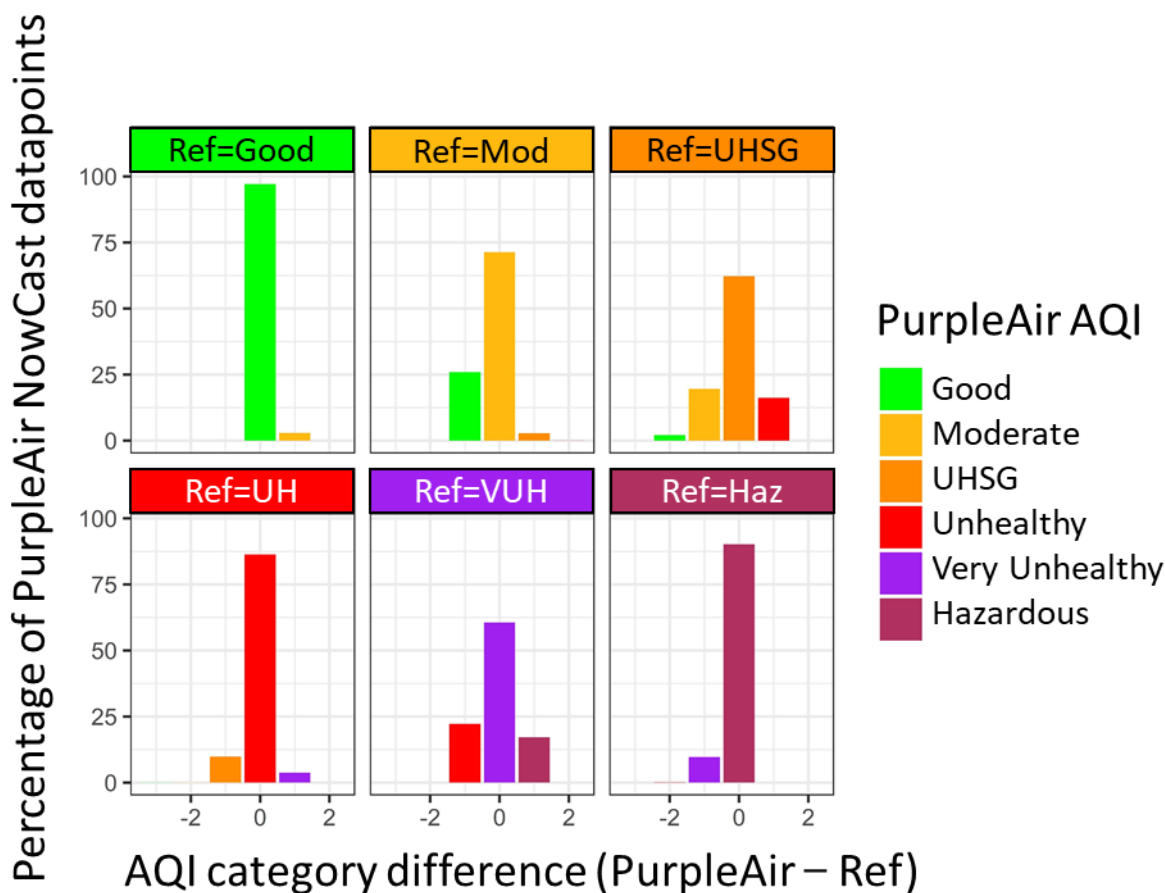


Figure 3. Percentage of the time that the PurpleAir NowCast AQI is the same as or different by 1 or 2 NowCast AQI categories. This is binned by the reference NowCast AQI category. It includes data using both withholding methods.

For this paper, we have also considered the Nilson equation [28]. This equation is in use on a $PM_{2.5}$ map of Canada, showing the FEM monitors, along with the PurpleAir and AQ Egg sensors (<https://cyclone.unbc.ca/aqmap/>, accessed on 26 July 2022). Although the correction appears to perform well at low ($\sim <25 \mu\text{g}/\text{m}^3$) and extremely high concentrations, ($\sim >500 \mu\text{g}/\text{m}^3$) it overestimates the values at many concentrations in between (Figure 4). When the Nilson equation is compared to the U.S.-wide correction (in use up to $300 \mu\text{g}/\text{m}^3$), the equations diverge above $\sim 15 \mu\text{g}/\text{m}^3$, with the Nilson equation estimating higher concentrations of $PM_{2.5}$ (Figure 5).

We fitted and tested a model of a similar form (Model F, Table 3) on the dataset in this study, which resulted in significant overestimates between the breakpoint to unhealthy values for sensitive groups (UHSG) to the breakpoint to “Hazardous” AQI ($28\text{--}300 \mu\text{g}/\text{m}^3$, NMBE = 42% to 63%, Table S9). The equation developed on the dataset in this paper has slightly higher coefficients than the equation developed by Nilson, but the coefficients are within 10% (Figure S7 in the Supplementary Materials). The slightly higher coefficients suggest a higher PurpleAir/monitor ratio in our dataset, which may be due to a larger fraction of T640 and T640x data, used in the Nilson paper, leading to higher monitor concentrations in the denominator. In addition, the RH term is slightly stronger, suggesting slightly more hygroscopic growth in our dataset. The Nilson correction does not agree well with the correction that we have developed in this paper.

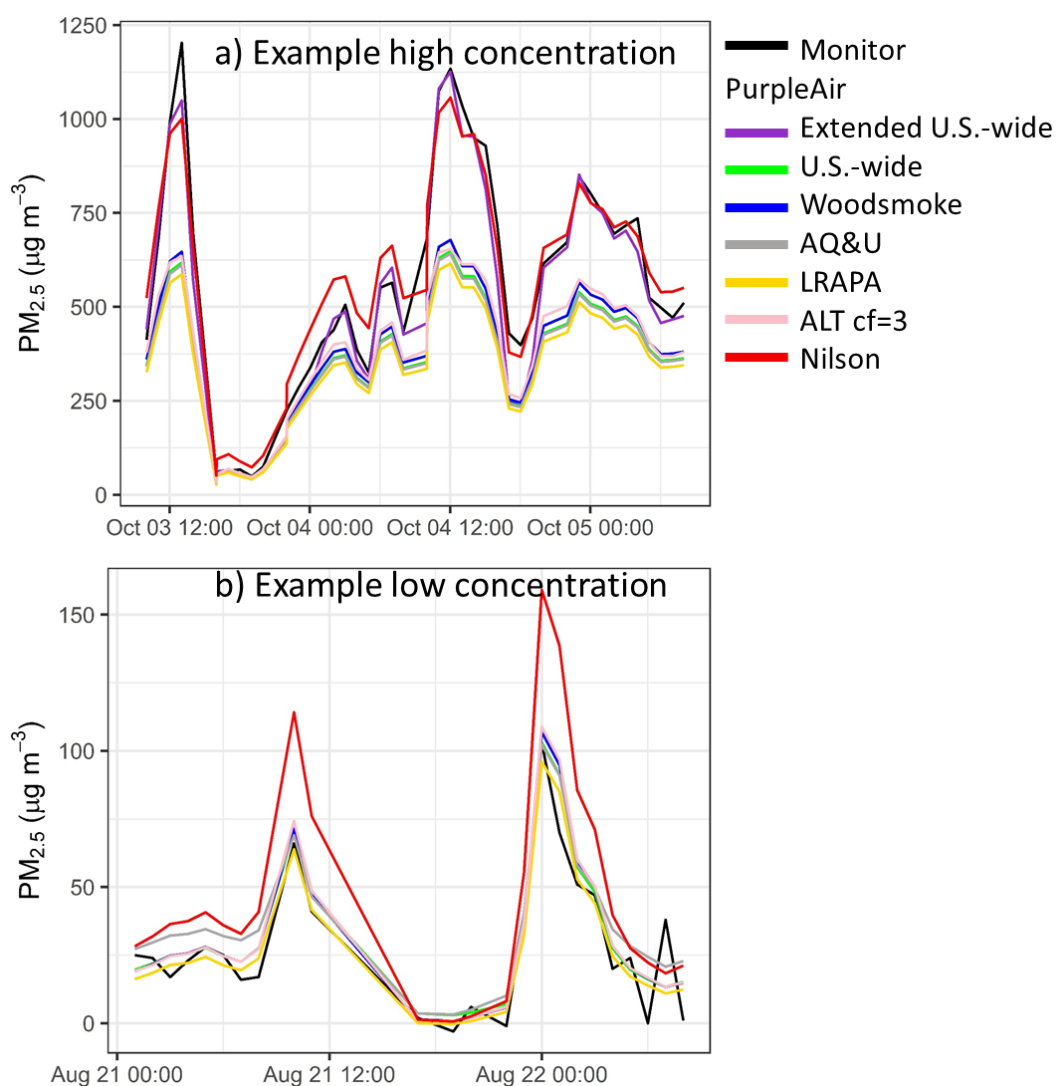


Figure 4. Example time series from the Forks of Salmon, CA showing the data that were corrected, based on different corrections on the PurpleAir map (Woodsmoke, AQandU, LRAPA, ALT cf = 3) and in the literature (Nilson).

4. Conclusions

Air sensors can provide additional data critical during smoke impacts. While the U.S.-wide correction developed previously improves the accuracy of hourly data up to $300 \mu\text{g}/\text{m}^3$, transitioning to a quadratic fit at higher concentrations keeps the NMBE to $\leq 10\%$ at each AQI breakpoint and at $500 \mu\text{g}/\text{m}^3$ (the Cal/OSHA respirator limit). The correction developed in this paper can be used to improve the performance of PurpleAir sensors in situations from typical ambient concentrations to extreme smoke. The equation developed in this paper is not comparable to other commonly used PurpleAir corrections that are focused on a narrower range of concentrations.

This work is an evaluation of a single air-sensor type and there are many additional sensors commercially available. The framework from this study may be used for additional air sensor types. It could be used to both develop corrections and better understand sensor performance over the full range of anticipated concentrations, where decisions must be made (e.g., $0\text{--}500 \mu\text{g}/\text{m}^3$). Understanding sensor performance over a wide range of concentrations is critical for an application where sensors will provide information during both smoke-impacted and typical ambient conditions. The findings from this paper may

also be relevant for other pollutant types, wherein understanding the performance over the full range of decision-relevant concentrations is important as well.

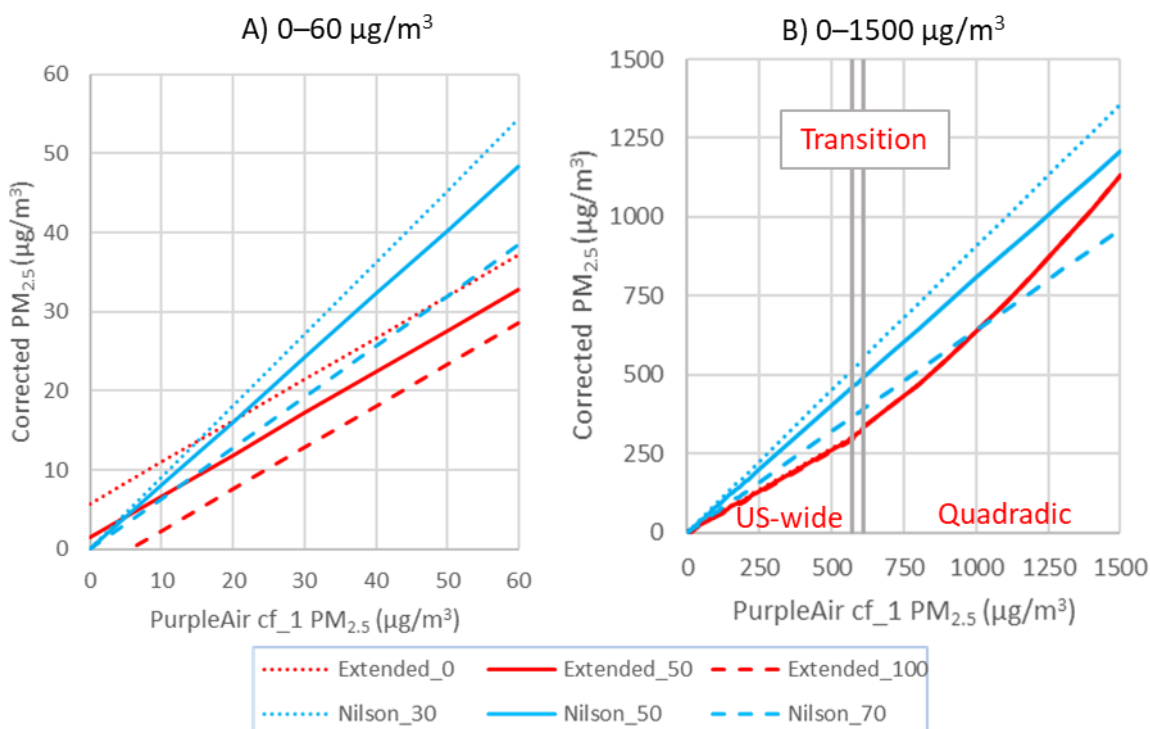


Figure 5. Disagreement between Nilson and the extended US-wide correction, plotted over the range of RH used in each correction, shown at low concentrations (A) and over the full range (B) with grey vertical lines showing the transition zone from the US-wide correction to the quadratic fit.

4.1. Limitations

Because some of the PurpleAir sensors in this work were identified from the AirNow fire and smoke map, we do not have any certainty of the accuracy of their location. This may lead to additional errors since they might not be truly collocated. Some sensor owners may specifically identify their sensor location inaccurately, to address privacy concerns. Sensors that were actually collocated (within <10 m) may have seen better agreement. While 3 km is farther than we would typically consider for collocation (typically <0.1 km), the 3 sites with longer distances still had strong correlations (hourly $R^2 = 0.94\text{--}0.96$), which was in line with those of the true collocations (hourly, $R^2 = 0.54\text{--}0.97$).

PurpleAir and the internal sensors are known to underestimate the values during dust events [17,35,56–58], which may have contributed to some of the errors at dust-impacted sites in this study. Dust may be harder to sample with these sensors because of the large particle losses in the inlet due to the low flow fans, particle loss due to internal turns in the sensor, lower light scattering to the mass ratio for larger particles, and the assumed size distribution used to convert light scattering from the sensor into mass that cannot adjust if larger particles are present [53,59–61]. Future air-sensor hardware or correction methods that could account for dust and the changing size distributions could lead to improved accuracy and would be a valuable addition.

This work did not specifically consider sensor drift and aging. There is some uncertainty in the long-term performance of these sensors, although the comparison of the duplicate Plantower sensors gives us more confidence in the measurements over time. Previous work done on PurpleAir sensors in California has suggested they can provide useful data for three years or more without substantial drift [62]. As the PurpleAir network ages, additional work should be done to understand any impacts on accuracy over the full range of concentrations.

Relative humidity data were missing from a small portion of the dataset (1%). We did not account for the accuracy of the RH measurement in this work, although past work has shown that the PurpleAir internal RH measurement is strongly correlated with true temperature and RH and has high precision [23,31,32]. If an RH sensor fails, a default value of 50% or a local average RH can be used as a substitute.

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