https://doi.org/10.5194/amt-2020-413
Preprint. Discussion started: 2 December 2020

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Development and Application of a United States wide correction for $PM_{2.5}$ data collected with the PurpleAir sensor

Karoline K. Barkjohn[1], Brett Gantt[2], & Andrea L. Clements[3]

[1]ORISE fellow hosted by the Office of Research and Development, U.S. Environmental Protection Agency 109 T.W. Alexander Drive Research Triangle Park, NC 27711, johnson.karoline@epa.gov

[2]Office of Air Quality Planning and Standards, U.S. Environmental Protection Agency, 109 T.W. Alexander Drive Research Triangle Park, NC 27711, gantt.brett@epa.gov

[3]Office of Research and Development, U.S. Environmental Protection Agency 109 T.W. Alexander Drive Research Triangle Park, NC 27711, clements.andrea@epa.gov

Correspondences to: Karoline K. Barkjohn (johnson.karoline@epa.gov)

Abstract. PurpleAir sensors which measure particulate matter (PM) are widely used by individuals, community groups, and other organizations including state and local air monitoring agencies. PurpleAir sensors comprise a massive global network of more than 10,000 sensors. Previous performance evaluations have typically studied a limited number of PurpleAir sensors in small geographic areas or laboratory environments. While useful for determining sensor behavior and data normalization for these geographic areas, little work has been done to understand the broad applicability of these results outside these regions and conditions. Here, PurpleAir sensors operated by air quality monitoring agencies are evaluated in comparison to collocated ambient air quality regulatory instruments. In total, almost 12,000 24-hour averaged $PM_{2.5}$ measurements from collocated PurpleAir sensors and Federal Reference Method (FRM) or Federal Equivalent Method (FEM) $PM_{2.5}$ measurements were collected across diverse regions of the United States (U.S.), including 16 states. Consistent with previous evaluations, under typical ambient and smoke impacted conditions, the raw data from PurpleAir sensors overestimate $PM_{2.5}$ concentrations by about 40% in most parts of the U.S. A simple linear regression reduces much of this bias across most U.S. regions, but adding a relative humidity term further reduces the bias and improves consistency in the biases between different regions. More complex multiplicative models did not substantially improve results when tested on an independent dataset. The final PurpleAir correction reduces the root mean square error (RMSE) of the raw data from 8 μg m^{-3} to 3 μg m^{-3} with an average FRM or FEM concentration of 9 μg m^{-3}. This correction equation, along with proposed data cleaning criteria, has been applied to PurpleAir $PM_{2.5}$ measurements across the U.S. in the AirNow Fire and Smoke Map (fire.airnow.gov) and has the potential to be successfully used in other air quality and public health applications.

1 Introduction

Fine particulate matter ($PM_{2.5}$, the mass of particles with aerodynamic diameters smaller than 2.5 μm) is associated with a number of negative health effects (Schwartz et al., 1996;Pope et al., 2002;Brook et al., 2010). Short-term and long-term exposures to $PM_{2.5}$ are associated with increased mortality (Dominici et al., 2007;Franklin et al., 2007;Di et al., 2017). Even at low $PM_{2.5}$ concentrations, significant health impacts can be seen (Bell et al., 2007;Apte et al., 2015) and small increases of only 1-10 μg m^{-3} can increase negative health consequences (Di et al., 2017;Bell et al., 2007;Grande et al., 2020). In addition to health effects, $PM_{2.5}$ can harm the environment, reduce visibility, and damage materials and structures (Al-Thani et al., 2018;Ford et al., 2018). Understanding $PM_{2.5}$ at fine spatial and temporal resolutions can help mitigate risks to human health and the environment, but the high cost and complexity of conventional monitoring networks can limit network density (Snyder et al., 2013;Morawska et al., 2018).

Lower cost air sensor data may provide a way to better understand fine scale air pollution and protect human health. Air sensors are widely used by a broad spectrum of groups from air quality monitoring agencies to individuals. Sensors offer the ability to measure air pollutants at higher spatial and temporal scales than conventional monitoring networks with potentially less specialized operating knowledge and cost. However, concerns remain about air sensor data quality (Clements et al., 2019;Williams et al., 2019). Typically, air sensors require correction to become more accurate compared to regulatory monitors. A best practice is to locate air sensors alongside regulatory air monitors to understand their local performance and to develop corrections for each individual sensor (Jiao et al., 2016;Johnson et al., 2018;Zusman et al., 2020). For optical particulate matter (PM) sensors, correction procedures are often needed due to 1) the changing optical properties of aerosols associated with both their physical and chemical characteristics (Levy Zamora et al., 2019;Tryner et al., 2019) and the local meteorological conditions including temperature and relative humidity (RH) (Jayaratne et al., 2018;Zheng et al., 2018) and 2) some models of air sensors having out of the box differences and low precision between sensors of the same model (Feenstra et al., 2019;Feinberg et al., 2018). Although collocation and local correction may be achievable for researchers and some air monitoring agencies, it is unattainable for many sensor users and community groups due to lack of access to regulatory monitoring sites.

PurpleAir sensors are a PM sensor package consisting of two laser scattering particle sensors, a pressure-temperature-humidity sensor (BME280), and a WiFi-enabled processor that allows the data to be uploaded to the cloud and utilized in real-time. The low cost of outdoor PurpleAir sensors ($230-$260 U.S. dollars) has enabled them to be widely used with thousands of sensors publicly reporting across the U.S. Previous work has explored the performance and accuracy of the PurpleAir sensors (Magi et al., 2019;Feenstra et al., 2019;Mehadi et al., 2019;Malings et al., 2019;Kim et al., 2019;Sayahi et al., 2019;Tryner et al., 2020a;Singer and Delp, 2018;Kelly et al., 2017;Li et al., 2020;Wang et al., 2020b;Gupta et al., 2018;Delp and Singer, 2020;Zou et al., 2020b;Stavroulas et al., 2020;Holder et al., 2020;Ardon-Dryer et al., 2020;Schulte et al., 2020;Zou et al., 2020a;Robinson, 2020;Bi et al., 2020) and their dual Plantower PMS5003 laser scattering particle sensors (He et al., 2020;Tryner et al., 2019;Kuula et al., 2019;Ford et al., 2019;Si et al., 2020;Zou et al., 2020b;Tryner et al., 2020b). Although not true of all types of $PM_{2.5}$ sensors, previous work with PurpleAir sensors and other models of Plantower sensors have shown that the sensors are precise, with sensors of the same model measuring similar $PM_{2.5}$ concentrations (Barkjohn et al., 2020a;Pawar and Sinha, 2020;Malings et al., 2019). However, extensive work with PurpleAir and Plantower sensors has often shown deficiencies in the accuracy of the measurement resulting in the need for correction. A number of previous corrections have been developed; however, they are typically generated for a specific region, season, or condition, and little work has been

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Preprint. Discussion started: 2 December 2020

done to understand how broadly applicable they are (Ardon-Dryer et al., 2020;Magi et al., 2019;Delp and Singer, 2020;Holder et al., 2020;Tryner et al., 2020a). Although location specific and individual sensor corrections may be ideal, the high precision suggests that a single correction across PurpleAir sensors may be possible. This is especially important since having multiple corrections can make it difficult for many sensor users to know which correction is best for their application.

In this work, we develop a U.S. wide correction for PurpleAir data which increases accuracy across multiple regions making it accurate enough to communicate the Air Quality Index (AQI) to support public health messaging. We use onboard measurements and information that would be available for all PurpleAir sensors, even those in remote areas far from other monitoring or meteorological sites.

2 Methods

2.1 Site identification

Data for this project came from 2 sources: 1) PurpleAir sensors sent out by EPA for collocation and 2) data volunteered by state, local and tribal (SLT) air monitoring agencies independently operating collocated PurpleAir sensors. PurpleAir sensors were sent out by EPA to capture a wide range of regions and meteorological conditions. Some sites are part of a larger project to evaluate the long-term performance of multiple sensor types across the U.S. and these sites needed high time resolution $PM_{2.5}$ along with gas measurements. This larger EPA project also included sites where agencies were already operating collocated PurpleAir sensors and volunteered to share their data for this work. In order to identify other collocated sensors, a survey of sites with potentially collocated PurpleAir sensors and regulatory $PM_{2.5}$ monitors was performed by identifying publicly available PurpleAir sensor locations within 50 meters of an active EPA Air Quality System (AQS) site reporting $PM_{2.5}$ data in 2017 or 2018. The 50-meter distance was selected because it is large enough to cover the footprint of most AQS sites and small enough to exclude most PurpleAir sensors in close proximity, but not collocated with, an AQS site. From a download of all active AQS $PM_{2.5}$ sites and PurpleAir sensor locations on August 20, 2018, 42 unique sites were identified in 14 states. From this list of public PurpleAir sensors potentially collocated with regulatory $PM_{2.5}$ monitors, we reached out to the appropriate SLT air monitoring agency to understand if these units were operated by the air monitoring agency and their interest in partnering in this research effort. If we could not identify the sensor operator, or if the sensor was not collocated at the air monitoring station, the sensor was not used in this analysis. In total, 50 PurpleAir sensors at 39 unique sites across 16 states were ideal candidates and included in this analysis (Table 1). These PurpleAirs were built by PurpleAir over two years' time (most units created between Aug 2017 and Sept 2019). However, we do not have information on when the internal components were manufactured by Plantower. The supplement contains additional information about each AQS site (Table S1) and each individual sensor (Table S2).

2.2 Air monitoring instruments and data retrieval

2.2.1 PurpleAir sensors

The PurpleAir sensor contains two Plantower PMS5003 sensors labeled as channel A and B that operate for alternating 10-second intervals and provide 2-minute averaged data (prior to May 30, 2019, this was 80-second averaged data).

Plantower sensors measure 90-degree light scattering with a laser using 680±10 nm wavelength light (Sayahi et al., 2019) and are factory calibrated using ambient aerosol across several cities in China (Malings et al., 2019).

In the 2-minute or 80-second data, occasionally, an extremely high temperature (i.e. 2147483447) or an extremely low temperature (i.e. -224 or -223) was reported, likely due to electrical noise or a communication error between the temperature sensor and the PurpleAir microcontroller. The high error occurred in 24 of 53 sensors but occurred infrequently (34 instances in ~10^7 points total) while the low error impacted only 2 sensors (1% of the full dataset). Temperature values above 540°C (1000°F) were excluded before calculating daily averages since error values were detected above this level. Similarly, the RH sensor occasionally read 255%, this problem was experienced by each sensor at least once but still occurred infrequently (1083 points out of ~10^7 total). No other values were found outside 0-100% in the 2-minute or 80-second data before averaging. These points were removed from the analysis before 24-hr averaging.

For the sites used in this work, the 2-minute (or 80-second) $PM_{2.5}$ data were averaged to 24-hours (representing midnight to midnight local standard time). A 90% data completeness threshold was used based on channel A, since both channels were almost always available together, where 80-second averages required at least 0.9*1080 points before 5/30/2019 or 2-minute averages required at least 0.9*720 points after 5/30/2019). This methodology ensures that the averages used are truly representative of daily averages reported by regulatory monitors.

The two Plantower sensors within the PurpleAir sensor (channels A and B) can be used to check the consistency of the data reported. As illustrated in Figure 1, 24-hour averaged $PM_{2.5}$ concentrations reported by channels A and B generally agree exceptionally well (e.g., AZ1 sensor). However, our observations suggest there are some sensors where the two channels show a systematic bias out of the box (e.g., AK3 is the most apparent example), one channel reports zeros (e.g., CA4), or when reported concentrations do not match for a time but then recover (e.g., KS2). Anecdotal evidence from PurpleAir suggests some disagreements may be caused by spiders, insects, or other minor blockages that may resolve on their own. Data cleaning quality control procedures were developed using the typical agreement between the A and B channels (expressed as percent error). Data points falling outside of the normal agreement range with 95% certainty (2 standard deviations equalling 61%) were flagged for removal. At low concentrations, where a difference of a few µg m^{-3} could result in a percent error greater than 100%, an absolute concentration difference threshold of 5 µg m^{-3}, previously proposed by Tryner et al. (2020), was effective at removing questionable observations but was not appropriate at higher concentrations where a 5 µg m^{-3} difference was more common but only represents a small percent difference. Therefore, data were cleaned using a combination of these quality control metrics; data were considered valid if the difference between channels A and B was less than 5 µg m^{-3} or 61%.

When a PurpleAir sensor is connected to the internet, data is sent to PurpleAir's data repository on ThingSpeak. Users can choose to make their data publicly viewable (public) or control data sharing (private). Agencies with privately reporting sensors provided application programming interface (API) keys so that data could be downloaded. PurpleAir PA-II-SD models can also record data offline on a microSD card; however, these offline data appeared to have time stamp errors from internal clocks that drift without access to the frequent time syncs available with access to WiFi so they were excluded from this

https://doi.org/10.5194/amt-2020-413
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project. Data were downloaded from the ThingSpeak API using Microsoft PowerShell at the native 2-minute or 80-second time resolution and were saved as csv files that were processed and analysed in R (R Development Core Team, 2019).

The Plantower sensor reports estimated PM mass of particles with aerodynamic diameters <1 µm (PM_1), $PM_{2.5}$, and mass of particles with aerodynamic diameters <10 µm (PM_{10}). These values are reported in two ways, labeled as cf_1 and cf_atm, in the PurpleAir dataset which match the "raw" Plantower outputs. PurpleAir previously had these cf_1 and cf_atm column labels flipped in the data downloads (Tryner et al., 2020a), but for this work we have used the updated labels. The two data columns have a [cf_atm]/[cf_1] = 1 relationship below roughly 25 µg m^{-3} (as reported by the sensor), and then transitions to a 2/3 ratio at higher concentration ([cf_1] concentrations are higher). The cf_atm data, displayed on the PurpleAir map, is a lower measurement of $PM_{2.5}$ and will be referred to as the "raw" data in this paper when making comparison between initial and corrected datasets.

2.2.2 Federal Reference Method (FRM) and Federal Equivalent Method (FEM) $PM_{2.5}$

24-hour averaged $PM_{2.5}$ reference data was downloaded for the 39 collocation sites from the AQS database on February 20, 2020 for both FRM and FEM regulatory monitors. Collocation data was collected from 9/28/2017 (the earliest data at which the first collocated PurpleAir sensor was installed among the sites used in this study) through to the most recent quality assured data uploaded by each SLT agency (nominally 1/13/20). The 24-hour averages represent concentrations from midnight to midnight local time from either a single 24-hour integrated filter-based FRM measurement or an average of at least 18 valid hours of continuous hourly-average FEM measurements (75% data completeness). In our analysis, we included sample days flagged or concurred-upon as exceptional events to ensure that days impacted by wildfire smoke or dust storms with very high $PM_{2.5}$ concentrations would be accounted for in the correction.

National Ambient Air Quality Standards (NAAQS) sets a 24-hour average standard for $PM_{2.5}$ so the PurpleAir sensor and FRM or FEM comparison used daily data. This also allows for comparison of PurpleAir data to both FRM and FEM $PM_{2.5}$ measurements, which are expected to provide near-equivalent measurements at this time averaging interval. The use of 24-hour averages also benefits from the 1) improved inter-comparability between the different FEM instruments (Zikova et al., 2017), and 2) avoidance of the variability in short-term (1-minute to 1-hour) pollutant concentrations compared to longer term averages as used in the NAAQS (Mannshardt et al. 2017).

2.3 Model input considerations

In order to build a data correction model that could easily be applied to all PurpleAir sensors, only data reported by the PurpleAir sensor (or calculated from these parameters) were considered as model inputs. We first considered a number of redundant parameters (i.e. multiple $PM_{2.5}$ measurements, multiple environmental measurements) using linear regression; once we selected the parameters that explained the most variance, we considered a number of increasingly complex models where parameters were included as additive terms with coefficients or where they were multiplied with each other to form more complex models.

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This included consideration of $PM_{2.5}$ concentrations (both [cf_1] and [cf_atm] data columns) and binned particle counts, in addition to temperature, and RH data. This work also considered dewpoint as calculated from the reported temperature and RH data. Pressure was not a reported variable for 10% of the dataset and was therefore not considered as a possible correction parameter. It is important to note that the meteorological sensor in the PurpleAir sensor is positioned above the particle sensors nestled under the PVC cap resulting in temperatures that are higher (2.7 to 5.3°C) and RH that is drier (9.7% to 24.3%) than ambient conditions (Malings et al., 2019;Holder et al., 2020) but which may be closer to what is experienced by the aerosol during measurement. In addition, these internal measurements have been shown to be strongly correlated with reference temperature and RH measurements with high precision (Holder et al., 2020). Although not as accurate as the reference measurements, the PurpleAir temperature and RH measurements are good candidates for inclusion in a linear model because they are well correlated with reference measurements and may more closely represent the particle drying that occurs inside the sensor. In addition, using onboard measurements and information that would be available for all PurpleAir sensors, allows us to gather corrected air quality data from all PurpleAirs, even those in remote areas far from other air monitoring or meteorological sites. Initially, each potential model input, or parameter, was evaluated separately using simple linear regression and then using more complex combinations (e.g., RH+T) to determine which parameter and combinations of parameters explained most of the variance (i.e., R^2_{adj}). In a multiple linear regression, all independent variables should be independent; however, much previous work has used models that incorporate temperature, RH, and dewpoint that are not independent (Malings et al., 2019;Magi et al., 2019).We have considered these models since they have been used in the literature and have also considered models with interaction terms (i.e. $RH*T*PM_{2.5}$) in order to account for inter-dependence between terms. The 24-hour FRM or FEM $PM_{2.5}$ concentrations were treated as the independent variable (plotted on x-axis) allowing the majority of error to reside in the PurpleAir concentrations. Subsequently, several of the best performing model forms were validated using withholding methods as described in the next section.

2.4 Model validation

Building the correction model based on the full dataset could lead to model overfitting so two different cross-validation structures were used: 1) "leave-out-by-date" (LOBD) and 2) "leave-one-state-out" (LOSO). For the LOBD model validation method, the project time period was split into 4-week periods with the last period running just short of 4 weeks (24 days). Each period contained between 179 and 2,571 24-hr data points with typically more sensors running continuously during later chunks as more sensors were deployed and came online over time. Thirty periods were available in total and, for each test-train set, 27 periods were used to train the correction model while three periods were selected to test the correction model. Models were generated for all 27,000 combinations of test data. For the LOSO model validation method, the correction model was built based on sensors from all but one state and then the model was tested on data from the withheld state. This resulted in 16 unique models since there are 16 states represented in this dataset. The LOSO method is useful for understanding how well the proposed correction may work in states that are not represented in our dataset. The performance of each correction method on the test data was evaluated using the root mean square error (RMSE), the mean bias error (MBE), the mean absolute error (MAE), and the Spearman correlation (ρ). Equations for these statistics are provided in the SI (Section S1). To compare statistical difference between errors t-tests were used to compare normally distributed datasets (as determined by Shapiro-Wilk) and Wilcoxon Signed Rank tests were used for nonparametric datasets with a significance value of 0.05. Data analysis for this project was completed in R (R Development Core Team, 2019).

The performance of the selected model is summarized by region. Sites were first divided by the National Oceanic and Atmospheric Administration's (NOAA) U.S. Climate Regions (NOAA, 2020;Karl and Koss, 1984) and then were grouped in to broader regions (Figure 2) if the relationships between the sensor and FEM or FRM measurements were not significantly different. Lastly, we summarize the performance of the sensors across the U.S. using the U.S. daily AQI categories (Federal Register, 1999).

3 Results & discussion

3.1 Raw data removed by cleaning

For correction model development, it was important to start with the most robust dataset possible. For this work, 24-hour averages were excluded from the dataset when the PurpleAir A and B channel [cf_1] $PM_{2.5}$ concentrations differed by more than 5 µg m^{-3} and 61% (two standard deviations of the percent error). This resulted in removal of only 0-47% of the data from individual sensors (Figure 1, Table A3) and 2.1% of the data in the full dataset. Most sensors had little to no removal (N= 48, <10% removed); 5 sensors had 10% to 47% removed (AK2, AK3, CA4, CA7, WA5). Of these sensors, 3 had average channel differences of more than 25% (27-45%), after applying 24-hour AB channel comparison removal criteria (AK3, CA7, WA5). These sensors, representing 3% of the dataset, were removed from further analysis because of the additional error they could add into the correction model building. A discussion of the impacts of these quality assurance steps on the final dataset, after correction, is discussed in Section 4.5.1.

In some cases, additional quality control checks on either the part of PurpleAir or the purchaser could identify problem sensors before they were deployed; this was done by EPA by collocating all sensors for a few days before deploying across the U.S. to identify any major issues, and may have been done by other agencies. Previous work with PurpleAir sensors has often excluded sensors for poor correlation between channels but our work shows that this will not be sufficient for ensuring good data quality. Previous work with PurpleAir sensors reported that 7 of 30 sensors (23%) were defective out of the box and exhibited low Pearson correlations (r<0.7) in a laboratory evaluation (Malings et al., 2019). Ten of 53 sensors (19%) in our study had r<0.7 (i.e. AK2, CA3, CA4, CA7, IA10, KS2, WA2, WA3, WA5, WI2); only two of these were removed due to large average percent differences after removing outliers where A and B channels did not agree (i.e. WA5, CA7). Six of these 10 sensors had ≤4% of the data removed by data cleaning steps and their Pearson correlation improved to ≥0.98 (from r<0.7) suggesting that the low correlation was driven by a few outlier points. Some sensors with low initial Pearson correlations had high Spearman correlations (range: 0.69 to 0.98); this suggests, again, that the low performance was due to a few outlier points. These results highlight that sensors may fail checks based on Pearson correlation or overall percent difference thresholds due to only a small fraction of points often making them poor indicators of overall sensor performance. The removal of outliers between the A and B channels can greatly improve agreement between sensors and between sensors and reference instruments.

3.2 Data summary

After excluding poorly performing sensors (N=3), 50 PurpleAir sensors had collocated data. These sensors were located in 16 states across 39 sites (Figure 2, Table 1). Additional details on the individual sensors and AQS sites can be found in the Supplement (Table S2, S3). Some sites had several PurpleAir sensors running simultaneously (N=9) and one ran multiple sensors in series. Some states had more than two years of data while others had data from a single week or season. Median state-by-state $PM_{2.5}$ concentrations, as measured by the FRM or FEM, ranged from 4-10 µg m^{-3}. A wide range of $PM_{2.5}$ concentrations was seen across the dataset with a maximum 24-hour average of 109 µg m^{-3} measured in California; overall the median $PM_{2.5}$ concentration of the dataset was 7 µg m^{-3} (inter quartile range: 5-11 µg m^{-3}, average(sd): 9(5) µg m^{-3}). Sensors were located in several U.S. climate zones (NOAA, 2020;Karl and Koss, 1984) resulting in variable temperature and RH ranges.

Initially, there were 10,907 days of collocated data from Iowa which was 55% of the entire collocated dataset. In order to better balance the dataset among the states, and to avoid oversampling, the number of days from Iowa was reduced to equal the size of the California dataset, the state with the next largest amount of data (29% of the entire collocated dataset). When reducing the Iowa dataset, the high concentration data were preserved. Although high 24-hour $PM_{2.5}$ averages occurred less frequently, they may have larger public health consequences and be of greater interest to communities. In order to preserve more of the high concentration data, the Iowa PurpleAir $PM_{2.5}$ data were split into 10 bins from 0-64 µg m^{-3} by 6.4 µg m^{-3} increments. Since there were less data in the higher concentration bins, all data in bins 6-10 (≥25 µg m^{-3}) were included and an equal number of randomly selected data points was selected from each of the other 4 bins (N=649). The subset and full complement of Iowa data were compared visually and the distributions of the temperature and RH for both datasets were similar (Figure S1).

3.3 Determining parameters and equations to use

3.3.1 Parameters considered

First, we considered redundant parameters to identify which model parameters and model forms to explore further. The equations and R^2_{adj} for each, along with the models selected as best of each complexity, are summarized in Table S4. Initially, both columns of $PM_{2.5}$ data ([cf_1] and [cf_atm]) were considered as potential correction input parameters. The $PM_{2.5}$ [cf_1] data explained more of the variation than the [cf_atm] data ($R^2_{adj[cf\_1]}$=0.781, $R^2_{adj[cf\_atm]}$=0.765) (Figure 3). The modest change in R^2_{adj} reflects the fact that only 3.8% of the dataset has FRM or FEM $PM_{2.5}$ concentrations greater than 20 µg m^{-3} which is where these two data columns exhibit a different relationship (Section 2.2.1) . Previous work with Plantower sensors in the U.S. has shown nonlinearity at higher concentrations >10-25 µg m^{-3}, which we do not see, which appears due to the use of the [cf_atm] data in the previous work (Stampfer et al., 2020;Malings et al., 2019;Kelly et al., 2017).

In addition to $PM_{2.5}$ concentration data, the PurpleAir sensors also provide the count of particles per 0.1 liter of air above a specified size in µm (i.e. >0.3, >0.5, >1.0, >2.5, >5.0, >10 µm); however, these are actually calculated results as opposed to actual size bin measurements (He et al., 2020). Nonetheless, previous studies have suggested that the binned particle count data from the Plantower is more effective at estimating $PM_{2.5}$ concentrations than the reported $PM_{2.5}$ concentration data from the newer Plantower PMSA003 sensor (Zusman et al., 2020); therefore binned particle counts were considered. First, binned particle count data from channels A and B were averaged. Then, the bins as reported by the PurpleAir (Eq. 1) were considered where s_1-s_6 are the fitted model coefficients for the corresponding binned particle counts and i is the fitted model intercept.

$$(\text{FRM or FEM } PM_{2.5}) = (s_1{*}B_{>0.3}) + (s_2{*}B_{>0.5}) + (s_3{*}B_{>1.0}) + (s_4{*}B_{>2.5}) + (s_5{*}B_{>5.0}) + (s_6{*}B_{>10.0}) + i \quad (1)$$

However, a regression between the sum of each bin variable and the FRM or FEM $PM_{2.5}$ resulted in a lower R^2 than the [cf_1] $PM_{2.5}$ channel ($R^2_{RawBins}$=0.769). Using the size bin data may also be less practical for some real-time applications as it would require importing additional columns of data (i.e. 6 bins x 2 sensors = 12 columns as opposed to just 2 $PM_{2.5}$ columns).

Temperature and RH from the PurpleAir sensor and a calculated dewpoint were considered based on previous studies (Malings et al., 2019). 24-hour PurpleAir averages with missing temperature or RH data were excluded from the following analysis (1%). Including an additive, linear RH term to a model already including the [cf_1] PurpleAir $PM_{2.5}$ data yielded the strongest correlation ($R^2_{AddRHTerm}$= 0.831) with dewpoint explaining less of the total variance than temperature ($R^2_{AddDewpointTerm}$=0.788, $R^2_{AddTempTerm}$=0.792). Since the linear model with RH has the best performance of these combinations, it will be further considered in the next section.

As in previous studies with Plantower sensors, the PurpleAir sensors appear to overestimate $PM_{2.5}$ concentrations at higher RH (Tryner et al., 2020a;Magi et al., 2019;Malings et al., 2019;Kim et al., 2019;Zheng et al., 2018). Overestimation was observed in our dataset before correction as shown in Figures S2 and S3 with overestimation increasing between 30 and 80%.There are few 24-hr averages above 80% RH so there is more uncertainty in the relationship above that level although it appears to level off. To address this, previous studies often used a nonlinear correction as opposed to a correction that changes linearly with RH (Stampfer et al., 2020;Tryner et al., 2020a;Malings et al., 2019;Kim et al., 2019;Zheng et al., 2018;Lal et al., 2020). A nonlinear RH model was tested by adding a $RH^2/(1\text{-}RH)$ term (see Eq. 2) similar to what has been used in past work for Plantower sensors and other light scattering measurements (Tryner et al., 2020a;Malings et al., 2019;Chakrabarti et al., 2004;Zheng et al., 2018;Zhang et al., 1994;Day and Malm, 2001;Soneja et al., 2014;Lal et al., 2020;Barkjohn et al., 2020b). In Eq. 2, PA is the PurpleAir $PM_{2.5}$ [cf_1] data and $PM_{2.5}$ is the concentration provided by the collocated FRM or FEM.

$$PA = s_1{*}PM_{2.5} + s_2\frac{RH^2}{(1-RH)}{*}PM_{2.5} + s_3{*}\frac{RH^2}{(1-RH)} + i \quad (2)$$

However, the $RH^2/(1\text{-}RH)$ term explained less variation than using the same equation with just RH instead of the nonlinear RH term (nonlinear RH: R^2=0.782, RH term: R^2=0.831) so this model form will not be used moving forward. This result suggests that there may be large variations in aerosol properties and meteorology in this nationwide dataset which are not well captured just by considering hygroscopicity. This term may be more significant in localized areas with high sulfate and nitrate concentrations where aerosol hygroscopicity plays an important role.

We next tried using a combination of two of the three basic environmental parameters (i.e. temperature, RH, dewpoint). Including both RH and temperature or RH and dewpoint resulted in a slightly higher R^2_{adj} than RH alone (both R^2_{adj}=0.832) while including dewpoint and temperature explained less variance than the RH alone (R^2_{adj}=0.827). Using all 3 terms in the model did not improve performance (R^2_{adj}=0.832) which may be expected as they include redundant information. Moving forward, only temperature and RH were considered since the calculated dewpoint did not explain additional error and models including temperature and RH have been used in previous work (Magi et al., 2019).

Lastly since temperature, RH, and PurpleAir $PM_{2.5}$ concentrations were significantly correlated, we considered two models including interaction terms. One including the interaction only between RH and $PM_{2.5}$ and one including the interaction between RH, T and $PM_{2.5}$. Both models explained increasing amounts of variance and will be explored further in the next section.

3.3.2 Models considered

Having established that the [cf_1] $PM_{2.5}$ concentration, RH, and temperature parameters best described the nationwide dataset, these parameters were incorporated into five possible corrections equations which were explored further. In those equations, shown below, PA represents the PurpleAir $PM_{2.5}$ [cf_1] data $PM_{2.5}$ represents the $PM_{2.5}$ concentration provided by the collocated FRM or FEM, s_1-s_7 are the fitted model coefficients, i is the fitted model intercept, and RH and T represent the RH and temperature as measured by the PurpleAir sensors..

1. Simple Linear Regression

$$PA = s_1*PM_{2.5} + i \tag{3}$$

2. Multilinear with an additive RH term

$$PA = s_1*PM_{2.5} + s_2*RH + i \tag{4}$$

3. Multilinear with additive T and RH terms

$$PA = s_1*PM_{2.5} + s_2*RH + s_3*T + i \tag{5}$$

4. Multilinear with additive and multiplicative terms using RH and $PM_{2.5}$

$$PA = s_1*PM_{2.5} + s_2*RH + s_3*RH*PM_{2.5} + i \tag{6}$$

https://doi.org/10.5194/amt-2020-413
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5. Multilinear with additive and multiplicative terms using T, RH, and $PM_{2.5}$

$$PA = s_1*PM_{2.5} + s_2*RH + s_3*T + s_4*PM_{2.5}*RH + s_5*PM_{2.5}*T + s_6*RH*T + s_7*PM_{2.5}*RH*T + i \tag{7}$$

3.4 Model evaluation

Figure 4 shows the performance of the raw and corrected PurpleAir $PM_{2.5}$ data using the five proposed correction models for the full dataset ("ALL") or datasets of withheld dates (LOBD) or states (LOSO). Both MBE, which summarizes whether the total test dataset measures higher or lower than the FRM or FEM measurements, and MAE, which summarizes the error on 24-hr averages, are shown with these metrics along with additional statistics and significance testing shown in the supplement (Table S5, S6). Large reductions in MAE, and MBE are seen when applying a linear correction. Using LOBD, the MBE across withholding runs drops significantly from 3.3 to 0 µg m^{-3} with a similar significant drop, from 4.2 to 0 µg m^{-3}, for LOSO withholding as well. This is a large improvement considering the average concentration in the dataset is 9 µg m^{-3}. When applying an additive RH term (+RH), the MAE improves significantly by 0.2 µg m^{-3} for LOBD withholding but does not change significantly for LOSO. Median LOSO and LOBD MBE do not change significantly. The inter quartile range (IQR) improves for both metrics and withholding methods showing that models typically have more consistent performance across withheld datasets. MBE for "ALL" does not improve since building a model on the full dataset and applying it will always result in an MBE of 0 whether it is a linear or more complex model. Overall, the additive RH correction model improves performance over the linear correction.

Increasing the complexity of the model (Eq. 5-7) shows similar performance to the additive RH model with no further improvements in MAE, MBE, or RMSE for LOSO withholding. Improving LOSO performance is of higher importance because there are some parts of the country that are not including in our model building dataset and this allows us to understand whether the model is likely to improve performance in other parts of the country. Model coefficients become more variable for more complex models depending on the dataset that is excluded suggesting that individual states or short time periods may be driving some of the coefficients in the more complex models (Table S7). Since more complex models do not improve median MAE, MBE, or RMSE for LOSO withholding and since more complex models will be applicable for a narrower window of conditions, the additive RH correction was selected as being most robust.

3.5 Selected correction model

In the end, the additive RH model (Eq. 4) seems to optimally summarize a wide variety of data while reducing error (MAE) compared to a simple linear correction. The following correction model (Eq. 8) was generated for the full dataset where PA is the average of the A and B channels from the higher correction factor (cf_1) and RH is in percent.

$$PM_{2.5} = 0.524*PA_{cf\_1} - 0.0852*RH + 5.72 \tag{8}$$

https://doi.org/10.5194/amt-2020-413
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This work indicates that only an RH correction is needed to reduce the error and bias in the nationwide dataset. Some previous single site studies found temperature to significantly improve their $PM_{2.5}$ prediction (Magi et al., 2019;Si et al., 2020). A temperature factor may help account for some local seasonal or diurnal patterns in aerosol properties within smaller geographical areas which may vary across the U.S. as is suggested, to an extent, by the difference in temperature model coefficients (Table S7). These, more local variations may be why temperature does not largely reduce error and bias in the nationwide dataset. Figure 5 shows the residual error in each 24-hour corrected PurpleAir $PM_{2.5}$ measurement compared with the temperature, RH, and FRM or FEM $PM_{2.5}$ concentrations. Error has been reduced compared to the raw dataset (Figures S2, and S3) and is unrelated to temperature, RH, and $PM_{2.5}$ variables. Some bias at very low temperature < -12°C and potentially high concentration (> 60 µg m^{-3}) may remain, but more data are needed to further understand this relationship.

3.5.1 Error in corrected data

Uncorrected PurpleAir sensors in this work overestimate $PM_{2.5}$ across U.S. regions (MBE greater than 0 µg m^{-3}; Figure 6). Figure 6 shows the regional performance as displayed on PurpleAir.com ("raw"), with a linear correction, and with the final selected additive RH correction (Eq. 8). Linear regression improves the RMSE in each region and the MBE also decreases in all regions except for Alaska. When adding the RH term to the linear regression, the bias is further reduced across all regions and the RMSE improves across all regions except for the Southeast where it increases slightly (<10%). Alaska shows the strongest underestimate which is only 1 µg m^{-3} on average. However, there are times were strong underestimates are seen under the one to one line after correction. These days where the PurpleAir sensors strongly underestimates the $PM_{2.5}$ concentration (by >5 µg m^{-3}) occur in the winter between November and February with subfreezing temperatures (-1 to -25 C). Plantower reports that the operating range of the sensors is -10 to 60 C so this may contribute to the error (Plantower, 2016). However, other states see subfreezing temperatures (6% of U.S. dataset) but most of this subfreezing data from other states does not have a strong negative bias (>98%). This could suggest unique winter particle properties or sensor performance in Fairbanks. The particles may be too large or too small to be efficiently sampled. However, information on particle size distribution is not available.

We have also provided state by state performance results in the SI (Section S2 and Figure S4). However, it is important to note that the reported performance may not accurately summarize state-wide performance in states with less than a year of data or those with a limited number of collocation sites.

Figure 7 shows the AQI as generated by the corrected PurpleAir (in colors) versus the AQI generated by the FEM or FRM with vertical lines indicating the break points between categories. With correction, the PurpleAir sensors report the correct AQI category 91% of the time while underestimating by one category 3% of the time and overestimating by one category 5% of the time. Many of these categorical disagreements occur near the AQI category break points where the estimates between the sensor and FEM or FRM measurements are within a few µg m^{-3} but this difference breaks the concentrations into different categories. In the moderate AQI category, as measured by the FEM or FRM, we see examples (in orange) where the PurpleAir shows large overestimates near the border between the good and moderate categories. These points represent 0.1%

of the total dataset and are from sensors in Washington and California during times in both the summer (August) and winter (November-January). This overestimate suggests that the PurpleAir is measuring more light scattering per mass than is typical in the U.S. Future work is needed to identify the factors affecting the strong sensor overestimates during these short time periods. From a public health perspective, however, there is more concern when the sensor strongly underestimates the $PM_{2.5}$ AQI.

There is also some underestimation in the moderate category. There are daily AQI values near the transition between moderate and unhealthy for sensitive groups where the PurpleAir is still in the good category (green). These occur primarily in the West (California). Past work has shown that PurpleAir sensors, and their internal Plantower PMS5003 sensors, underestimate $PM_{2.5}$ mass from larger particles including during dust impacted days (Kuula et al., 2020;Robinson, 2020;Kosmopoulos et al., 2020). Dust impacts may be driving the underestimates on these days in the West. Because it is harder for larger particles to be sampled by the low flowrate fans, especially under higher windspeeds, and also because larger particles scatter less light per mass than smaller particles, this may be impossible to correct for with the hardware available on a PurpleAir (Duvall et al., 2020;Pawar and Sinha, 2020). Additional regional information from satellites or other sources may be able to improve these measurements in the future or more advanced sensor hardware may allow more accurate estimates. In all, this represents <1% of the dataset. Typically, the sensors provide accurate estimates of the AQI category and have the potential to provide additional spatial density across the U.S. where regulatory and AirNow monitors are not currently found.

3.5.2 Importance of QC procedures

This work did not seek to optimize QC procedures to balance data retention with data quality, instead it focused on generating a best-case dataset from which to build a model. However, we can consider the impact of these QC procedures on the data quality and their importance for future work. If we apply the selected correction to the data without excluding any times where the A and B channels disagree and do not take into account the number of points that are going into each daily average (i.e. completeness), we can begin to understand the importance of these criteria (Table 2, additional details Table S8). Using only the A or B channels, the RMSE is 87 and 161 µg m^{-3} respectively between the channel $PM_{2.5}$ data and the FRM or FEM data; there is no correlation between the A or B channel data and the FRM or FEM. Averaging the two channels slightly improves the comparison (RMSE=92 µg m^{-3}). Using the AB comparison and excluding points where they are different by 5 µg m^{-3} and 60% shows a large improvement in performance (RMSE A=4 µg m^{-3}, B=3 µg m^{-3}, AB_{avg}=4 µg m^{-3}) with a slight improvement in the worse performing channel when the two channels are averaged. We are unaware of a reason why the A and B sensors should respond differently so this is likely a random difference between the sensors in the A group and the B group. If we also add the 90% completeness criteria to the AB channel exclusion, we see a slight improvement in RMSE (RMSE=3 µg m^{-3}). In this work we also excluded three sensors because there was overall poor agreement between the A and B channels even after excluding individual sensors. When we exclude these three sensors, the overall performance changes very little (RMSE=3 µg m^{-3}). These results show that excluding individual points when there are large disagreements between the A and B channels can greatly improve sensor performance. Since both channels are needed for comparison, it makes sense to average the A and B channels to improve the certainty on the measurement. The data completeness control provides less benefit and may not be needed for all future applications of these correction methods. In addition, sensors with systematic offsets were uncommon and did not largely impact the overall accuracy, so the individual 24-hr point AB removal criterion (e.g. 5 µg m^{-3} and 61%) may be sufficient.

3.5.3 Comparison to existing correction equations

Lastly, we compared the U.S. wide correction equation to others currently available on the PurpleAir map and to recent smoke impacted corrections. The map currently defaults to displaying the raw [cf_atm] $PM_{2.5}$ data; however, a drop down also allows you to select from two corrections, the Lane Regional Air Protection Agency (LRAPA) correction or the AQ&U correction, both of which use this raw [cf_atm] data in their correction equations (Sayahi et al., 2019;Giles, 2020). The U.S. wide correction, presented here, instead uses the [cf_1] data. The difference between these two data channels was discussed in Section 3.2.1 and Figure 3.

The LRAPA correction is a basic linear equation developed by the Lane Regional Air Protection Agency in Oregon while the PurpleAir sensor was being impacted by wood smoke from home heating in the winter. It was developed specifically for LRAPA's local airshed. The LRAPA correction is similar to our U.S. wide correction equation without an RH term; $PM_{2.5} = 0.5*PA_{cf\_atm} - 0.66$ (LRAPA, 2018). Assuming an RH of 70%, both corrections would yield similar results until roughly 25 µg m^{-3} when the [cf_atm] and [cf_1] start to disagree; however, in reality the relationships would vary as the RH varied. After this threshold, the LRAPA correction will result in lower concentrations which underestimate $PM_{2.5}$ as measured by the FRM or FEM in our dataset by about 33%. Applying this correction to our dataset results in an underestimate of $PM_{2.5}$ by 3 µg m^{-3} (34%) on average with more scatter as quantified by the RMSE (LRAPA= 4 µg m^{-3}, US correction=3 µg m^{-3})

The AQ&U correction is a linear correction developed for Salt Lake City, UT (Sayahi et al., 2019). The AQ&U correction is updated as additional data becomes available and is, at the time of this article, $PM_{2.5}=0.778*PA_{cf\_atm}+2.65$ (Sayahi et al., 2019). At high concentration (>25 µg m^{-3}) the slope in the AQ&U and U.S. wide corrections are fairly similar (i.e. [AQ&U] $0.778*PA_{cf\_atm}$=[U.S. wide equation] $0.52*PM_{cf\_1} = 0.52*3/2*PM_{cf\_atm} = 0.795*PA_{cf\_atm}$); at lower concentrations the AQ&U correction may provide somewhat higher estimates, although, it will depend on the RH. Applying this correction to our dataset results in an overestimate of $PM_{2.5}$ of 4 µg m^{-3} (51%) with more scatter as quantified by the RMSE (AQ&U=6 µg m^{-3}, U.S. correction=3 µg m^{-3}).

Air sensors are potentially of the greatest use during wildland fire smoke impacted times (Holm et al., 2020;Durkin et al., 2020;Holder et al., 2020;Delp and Singer, 2020). A recent paper developed a smoke specific correction for $PM_{2.5}$ concentrations from PurpleAir sensors based on smoke impacts from multiple types of fires in the U.S. (Holder et al., 2020). This paper finds an equation of $0.51*PA_{cf\_1} - 3.21$. The slope is within 3% of that calculated for the U.S.-wide correction. In the smoke study, RH was found not to significantly improve the model. This lack of significance is likely because the data did not come from as diverse of locations and seasons as the U.S.-wide dataset. The median RH in Holder et al. was around 40% which would make the U.S. correction intercept +2.312. The intercepts differ by 5 µg m^{-3}. Since the U.S. correction was built on more low concentration data, it likely provides a better constrained estimate of intercept and this difference will be a small percent difference under high concentration smoke events. At a PurpleAir $PM_{2.5}$ concentration of 300 µg m^{-3}, the smoke correction would give an estimate of 150 µg m^{-3} while the U.S.-wide correction would give an estimate of 160 µg m^{-3}, a difference of only 6%. Another recent paper developed smoke adjustment factors, linear adjustments with zero intercepts, for a variety of fires in California and Utah ranging between 0.44 and 0.53 (Delp and Singer, 2020). The slope calculated in our study is also within this range. Although there was limited smoke data included in the analysis in this paper, the similarity between the correction generated here and under smoke impacted times suggests that this equation will work well under smoke conditions.

The U.S. wide correction developed in this work will provide a more accurate correction across the U.S. in comparison to these region-specific corrections. The U.S. correction is more robust in part because the RH term can help account for meteorological variation across the U.S.

3.6 Limitations and implications

Because PM sensors use an optically based detector, they will never be able to perfectly capture the $PM_{2.5}$ mass because of the many factors affecting the optical-mass relationship (Liu et al., 2008). However, there are a number of higher complexity optical methods that are used frequently with adequate accuracy (Heintzenberg et al., 2006;Chung et al., 2001). Nephelometers are used for routine monitoring in some parts of the U.S. (OR DEQ, 2020) and are frequently used in health effects research (Delfino et al., 2004). The Teledyne T640 and T640x and Grimm EDM 180 are optically based monitors have been approved as FEMs in the past decade (US EPA, 2016). Humidity tends to induce large errors in these types of measurements (Chakrabarti et al., 2004;Day and Malm, 2001) which is addressed using a dryer or humidity control in FEMs (US EPA, 2016). The PurpleAir sensor provides minimal humidity control due to the higher internal temperature caused by the small volume containing the electronics.

The only reason a single U.S. correction is possible is because the dual Plantower sensors within the PurpleAir sensor typically have strong precision. It would not be possible to develop a single correction for sensors with high error or more variability among identical units. In addition, having two Plantower sensors in each PurpleAir sensor enables a data cleaning step based on sensor health, where we compare the A and B channels and exclude data where they agree poorly (Section 3.2.1). Alternative approaches would be necessary for devices with only a single PM sensor. Similar approaches as conducted in this work could be applied to develop U.S. wide corrections for other sensors with collocation data from across the U.S. However, similar or better precision among identical units, and quality assurance methods that check sensor health and flag questionable data would be needed. Adding data from additional types of air sensors could further increase the spatial knowledge of air quality across the U.S. moving forward.

The proposed PurpleAir correction in this work relies on RH data and in some cases the internal RH sensor may drift or fail. Users have two options if no valid RH data is reported: 1) discard data when the RH is missing or 2) to assume a RH based on typical ambient conditions in the U.S. or specific geographical area. In our dataset, <1 % of the RH data was missing but this may happen more often for individual sensors or over time as RH sensors fail. There will be additional uncertainty in the measurement if the RH term is not available but substituting a value of 50% may limit this error. RH sensor drift should result in less error than full RH sensor failure and future work should further explore the performance of the RH sensor.

Although this dataset includes sites throughout the U.S. (see Figure 2), some regions are oversampled while others are undersampled. The oversampled areas include Iowa and California (especially the South Coast Air Basin) which together represent 58% of the dataset. Both Iowa and the South Coast Air Basin have a higher fraction of nitrate in $PM_{2.5}$ than many other areas of the U.S., which may impact the hygroscopicity of particles represented in this dataset. Utah in winter has a similar composition which may be why the AQ&U correction is comparable. Undersampled areas include North Dakota, Texas, and Pennsylvania where $PM_{2.5}$ may have different optical properties due to different air pollution emission sources. In addition, only three sites in the dataset are classified as rural sites. It may be beneficial to collocate additional sensors in rural areas especially as sensors may provide the most value where government monitors are sparse. Furthermore, other localized source-oriented locations such as near major roadways, airports, and ports are not well-represented in this dataset and may not be well characterized by our correction. The Alaska site is one location included in this work where additional collocated sensors, along with additional information about particle properties, could help to better understand whether the proposed correction can be improved. Future work may be able to develop additional correction factors based on aerosol types however, this may be challenging as a small subset of these sites have collocated chemical speciation network (CSN) data (Table S1). The applicability of this correction to areas outside of the U.S. is also uncertain because much higher concentrations of $PM_{2.5}$ (likely with different size distributions and chemical components) are common throughout the globe (van Donkelaar et al., 2016). In addition, there is uncertainty in how higher concentrations may damage sensors or lead to faster sensor aging, potentially requiring more regular maintenance and/or replacement (Wang et al., 2020a). Since PurpleAir sensors were operated by air monitoring agencies, the dataset used for this work is an ideal dataset with potentially better performance than PurpleAir sensors operated by the general public. Every sensor location was confirmed, unlike sensors on the PurpleAir map that may have been relocated, moved indoors, or assigned an incorrect location for privacy reasons. In addition, air monitoring agencies have taken care to appropriately site the PurpleAir sensors in places with good air flow which may not be the case for all community deployed sensors. Future work may be needed to explore how to identify and flag sensors with incorrect locations and poor siting. In some cases, the performance of the PurpleAir sensors used in this project was evaluated before deployment to check for any issues between the A and B channels when the sensors arrived from PurpleAir. In many cases, the agencies hosting the PurpleAir sensors check the data regularly and may immediately address performance issues. This may result in a higher data completeness and better performance between the A and B channels than would be seen by sensors operated by the general public; however, our AB comparison methodology should address potential AB differences in sensors operated by the public. The criteria for this work were specifically stringent so that the model would be built on reliable data. Future work could explore loosening the criteria for AB agreement and data completeness.

During regulatory monitoring, the site operator plays a significant role in annotating the site data, metadata, and in maintaining records that document the monitoring effort. Although we received some of these notes from agencies operating sensors for this project, we would not expect any of this data to be present for publicly available sensors on the PurpleAir map.

Since the insights of the site operator are not incorporated into the PurpleAir data from Thingspeak, the job of annotating the raw data record passes to the data analyst, someone with likely little on the ground knowledge of how the sensor is being operated, and some questions that arise about sensor performance will be impossible to answer. Although some automated checks like the A and B channel comparison can be applied, we will not be able to attain the same level of confidence as a monitor with a site operator documenting and quality assuring data.

There are still unknowns about sensor performance over the long-term and during extreme events. Large performance deteriorations were not seen in this dataset with sensors up to two years old, but more targeted analysis should be completed especially as the network continues to age. This work was conducted using 24-hour averages. It can be more challenging to develop accurate corrections using shorter time averaged data (e.g. 1-hour or 2-minute averages) due to limitations in FRM measurements and increased noise in higher time resolution FEM measurements. Additional work is currently being done to understand the performance of this correction when applied to shorter time averaging intervals and during high concentration smoke impacted events when public interest in air quality is high and health/environmental impacts may be of concern.

This correction equation is currently being applied to the low-cost sensor data (currently supplied by PurpleAir) on the AirNow Fire and Smoke Map (fire.airnow.gov) along with similar quality assurance methods on NowCast averaged data. This allows the public to see greater spatial variability in $PM_{2.5}$ AQI than would be available with only AirNow monitors. The AirNow Fire and Smoke Map will be updated based on user feedback and as additional data become available to improve the correction and quality assurance methods. This site was well received by state, local, and tribal partner air monitoring agencies and the public, and received over 7 million page views in the first three months. See a screenshot in the SI (S5).

4 Conclusions

This work developed an effective quality assurance methodology for cleaning $PM_{2.5}$ data from the PurpleAir sensor by removing poorly performing sensors and short-term outlier concentration measurements using channel A and B comparisons. The U.S. correction improves PurpleAir measurement performance, reducing the 24-hour averaged $PM_{2.5}$ data RMSE from 8 to 3 μg m^{-3} across the country. A single U.S. correction model for the PurpleAir sensor was developed which includes additive correction terms using [cf_1] $PM_{2.5}$ and on-board RH data. The correction model performed well when evaluated against regulatory measurements across the U.S. reducing the bias to ±3 μg m^{-3} when validated on a state-by-state basis (Figure 4) and reducing the bias to ±1 μg m^{-3} when evaluating by region. With correction, the PurpleAir reports the 24-hour averaged $PM_{2.5}$ AQI within 1 category 100% of the time and reports the correct category 92% of the time. Corrected $PM_{2.5}$ data from the PurpleAir sensor can provide more confidence in measurements of ambient $PM_{2.5}$ concentrations for a wide range of potential applications including exposure assessments and real-time public health messaging. PurpleAir $PM_{2.5}$ data with this U.S.-wide correction is currently displayed on a pilot data layer on the AirNow Fire and Smoke Map (fire.airnow.gov).

More work is needed to understand if similar corrections can be developed for other sensor types. If other highly precise sensors with duplicate measurements are identified, similar methodology could be used to develop data cleaning steps and a nationwide correction. However, it is recommended that sensors are first collocated with reference measurements across the

U.S. (i.e. FEM and FRM methods), ideally for a year or more to reduce uncertainties caused by seasonal influences, over a range of meteorological conditions, and across PM concentration ranges and source types. Most other sensor types do not contain duplicate $PM_{2.5}$ measurements this will make ensuring their data quality more challenging and more complex methods of data cleaning may be required for sensors without duplicate measurements, or similar data quality may not be possible. Developing correction methods quality assurance methodology for additional sensor types could further increase the amount of data available to communities, epidemiologists, decision makers, and others.

5 Data availability

Data will be available at https://catalog.data.gov/dataset/epa-sciencehub.

6 Author contribution

KB and AC conceptualized the work. KB and BG curated the data. KB completed the formal analysis, developed the methods and figure visualizations. AC acquired funding. KB, AC, BG wrote the original draft, reviewed and edited.

7 Competing interests

The authors declare that they have no conflict of interest.

8 Acknowledgments

This work would not have been possible without the partnership of many SLT air monitoring agencies and other partners, including: State of Alaska, Citizens for Clean Air (Alaska), Maricopa County Air Quality Department, San Luis Obispo County Air Pollution Control District, Mojave Desert Air Quality Management District, California Air Resources Board, Santa Barbara County Air Pollution Control District, Ventura County Air Pollution Control District, Colorado Department of Public Health and Environment, Delaware Division of Air Quality, Sarasota County Government, Georgia Environmental Protection Division, Iowa Department of Natural Resources, Polk and Linn County (Iowa) Local Programs, the State Hygienic Laboratory at the University of Iowa, Kansas Department of Health & Environment, Missoula County, Montana Department of Environmental Quality, Forsyth County Office of Environmental Assistance & Protection, Clean Air Carolina, Quapaw Nation, Oklahoma Department of Environmental Quality, Virginia Department of Environmental Quality, State of Vermont, Puget Sound Clean Air Agency, Wisconsin Department of Natural Resources. These agencies and organizations provided data and shared their experiences in using the PurpleAir sensors in their jurisdictions. We would also like to thank Sean Fitzsimmons at Iowa Air Quality Bureau, Ian VonWald who is an ORISE postdoc hosted by EPA, Samuel Frederick who is an ORAU student services contractor to EPA, and Amara Holder, Rachelle Duvall, and Gayle Hagler at EPA for their help. We thank PurpleAir for maintaining and managing the repository of public and private data. We thank Adrian Dybwad and the PurpleAir staff for their time discussing this work and the addition of this correction as an option on the PurpleAir website. We thank the United States Forest Service and EPA's AirNow team for the incorporation of the air sensor pilot data layer on the AirNow Fire and Smoke map. We are grateful to our referees for their constructive input.

https://doi.org/10.5194/amt-2020-413
Preprint. Discussion started: 2 December 2020

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This project was supported in part by an appointment to the Research Participation Program at the EPA ORD's Center for Environmental Measurements and Modeling (CEMM), administered by the Oak Ridge Institute for Science and Education through an interagency agreement between the U.S. Department of Energy and EPA.

9 Disclaimer

The views expressed in this paper are those of the author(s) and do not necessarily represent the views or policies of the U.S. Environmental Protection Agency. Any mention of trade names, products, or services does not imply an endorsement by the U.S. Government or the U.S. Environmental Protection Agency. The EPA does not endorse any commercial products, services, or enterprises.

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Table 1. Summary of the dataset used to generate the U.S. wide PurpleAir correction equation. $PM_{2.5}$ concentrations from both the FEM or FRM and the PurpleAir (PA), temperature (T) and relative humidity (RH) are summarized as median (min, max).

State	Start Date	End Date	# of PA	# of Sites	# of Days	FEM or FRM	FEM or FRM $PM_{2.5}$ (μg m^{-3})	PA $PM_{2.5}$ (μg m^{-3})	PA T (°C)	PA RH (%)
CA	11/29/2017	12/29/2019	13	12	3762	Both	6 (-2,109)	7 (0,250)	22 (6,42)	45 (2,100)
IA	9/29/2017	1/13/2020	9	5	3762	Both	10 (0,36)	19 (0,69)	11 (-27,35)	55 (21,100)
WA	10/16/2017	10/28/2019	3	3	1035	FEM	6 (0,41)	8 (0,89)	13 (-2,30)	63 (26,84)
AZ	11/9/2018	12/31/2019	3	3	895	Both	7 (1,43)	6 (0,74)	24 (9,44)	26 (5,73)
WI	1/1/2019	11/18/2019	6	4	811	Both	6 (1,32)	9 (1,64)	18 (-25,33)	53 (31,82)
NC	3/25/2018	10/24/2019	1	1	700	Both	7 (0,20)	13 (1,43)	25 (-1,35)	48 (16,79)
AK	11/7/2018	9/30/2019	3	1	369	FRM	4 (0,60)	4 (0,131)	8 (-25,29)	47 (21,76)
KS	3/13/2019	9/30/2019	3	1	306	FEM	9 (2,33)	11 (0,50)	24 (9,34)	52 (30,71)
DE	7/27/2019	11/18/2019	1	1	205	Both	7 (1,17)	9 (1,35)	25 (6,35)	51 (34,75)
OK	7/10/2019	11/18/2019	2	2	190	Both	9 (1,25)	11 (1,35)	30 (1,38)	57 (29,86)
GA	8/2/2019	11/18/2019	1	1	184	Both	9 (3,18)	15 (5,34)	29 (5,36)	55 (44,77)
VT	3/30/2019	9/30/2019	1	1	146	Both	6 (2,18)	8 (1,31)	24 (12,34)	52 (36,71)
FL	5/31/2019	9/30/2019	1	1	119	FEM	6 (3,17)	5 (1,25)	32 (29,35)	60 (49,73)
CO	8/22/2019	11/18/2019	1	1	113	both	7 (2,25)	6 (1,45)	18 (-5,32)	33 (18,70)
VA	10/27/2019	12/29/2019	1	1	30	FRM	5 (2,20)	10 (2,41)	12 (8,25)	48 (35,65)
MT	12/3/2019	12/10/2019	1	1	8	FEM	10 (5,15)	22 (6,36)	4 (2,6)	54 (42,62)
All	9/29/2017	1/13/2020	50	39	12635	both	7 (-2,109)	10 (0,250)	19 (-27,44)	51 (2,100)

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Table 2. Performance by quality assurance methods and corrections. Quality assurance (QA) criteria include excluding 24-hr averages where <90% of measurements are available (completeness), comparison of the A and B channels where data is excluded when the A and B channels are different by both 5 µg m^{-3} and 61% (AB), and the removal of 3 sensors that had poor agreement in the A and B channel after excluding 24-hr problematic points (problem sensors, details in section 4.1). Performance is compared for the individual channels (i.e. A, B) and as the average of the A and B channels (AB). Table S8 contains additional statistics.

QA criteria	correction	Channels	RMSE (µg m^{-3})	MAE (µg m^{-3})	MBE (µg m^{-3})
None	US	A	87	7	5
None	US	B	161	12	8
None	US	AB	92	9	7
Completeness	US	AB	38	3	1
AB	US	AB	4	2	0
AB, completeness	US	AB	3	2	0
AB, completeness, problem sensors	US	AB	3	2	0
AB, completeness, problem sensors	LRAPA	AB	4	3	-3
AB, completeness, problem sensors	AQ&U	AB	6	4	4

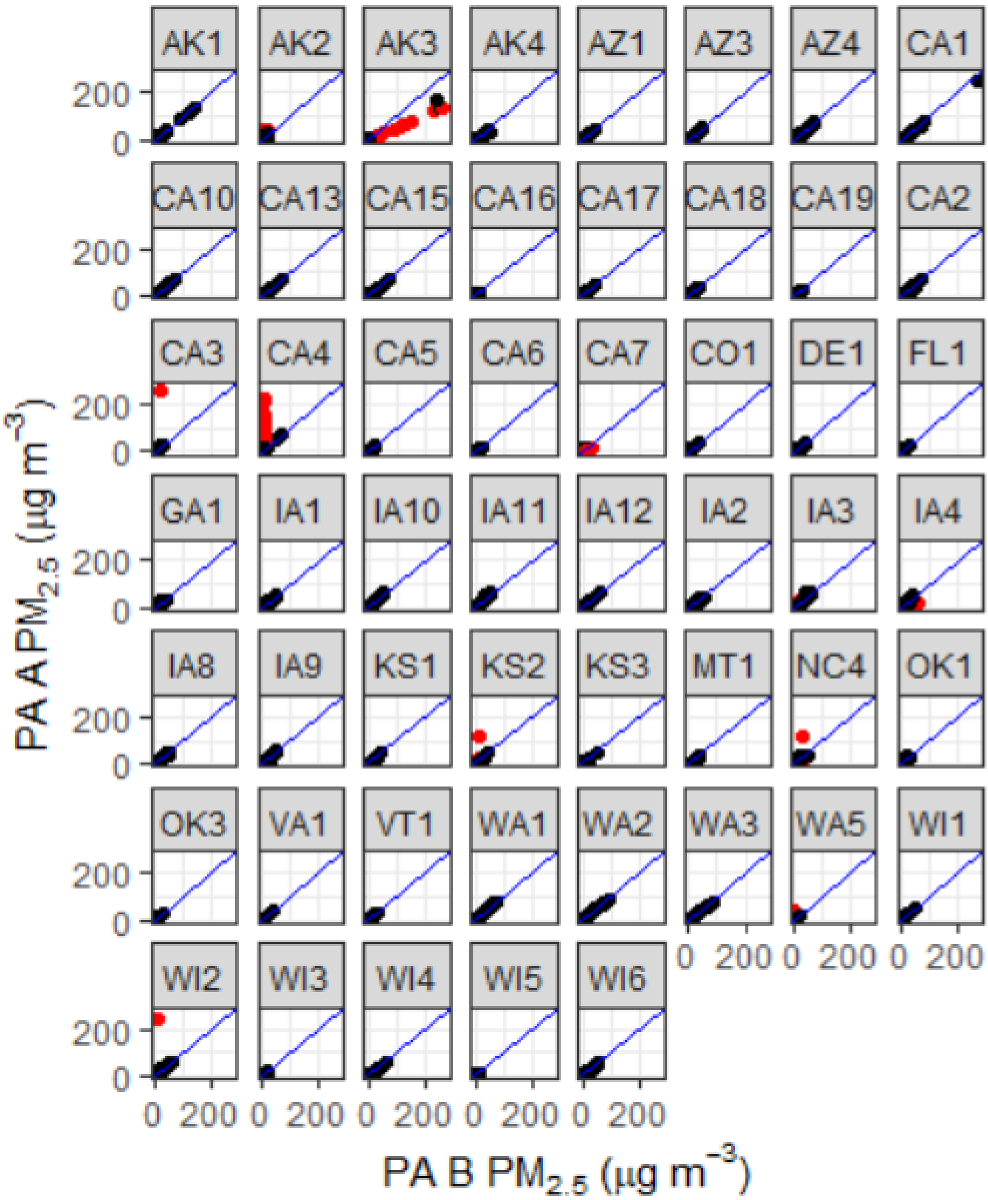

Figure 1. Comparison of 24-hour averaged $PM_{2.5}$ data from the PurpleAir A and B channels. Excluded data (2.1%) are shown in red and represent data points where channels differed by more than 5 μg m^{-3} and 61%. AK3, CA7, WA5 were excluded from further analysis.

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Figure 2. State, local, and tribal (SLT) air monitoring sites with collocated PurpleAir sensors. Includes regions used for
840 correction model evaluation.

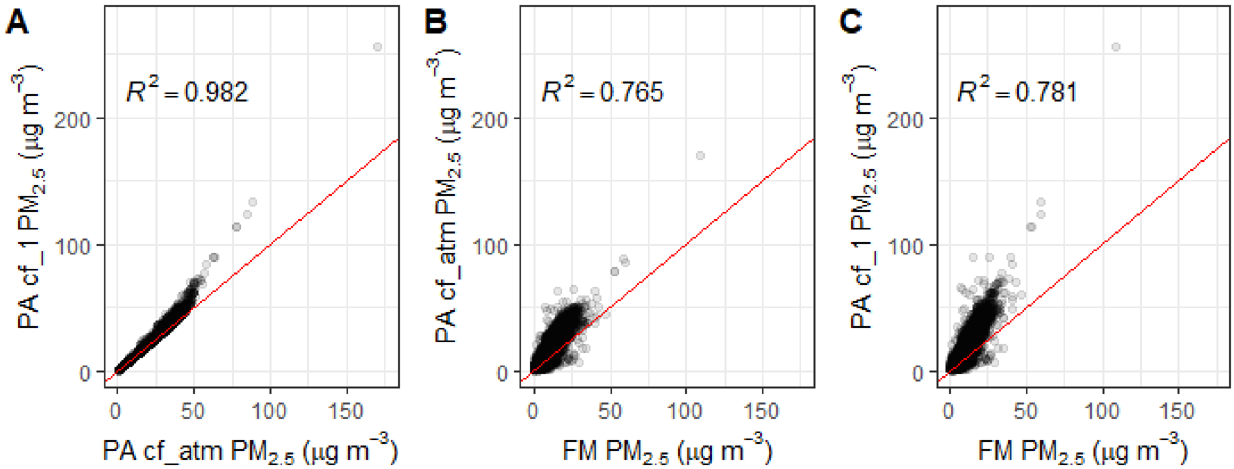

Figure 3. Comparison of the 24-hour raw PurpleAir (PA) cf_1 and cf_atm $PM_{2.5}$ outputs (A) and both outputs compared to the FEM or FRM $PM_{2.5}$ measurements (B and C) across all sites with the 1:1 line in red.

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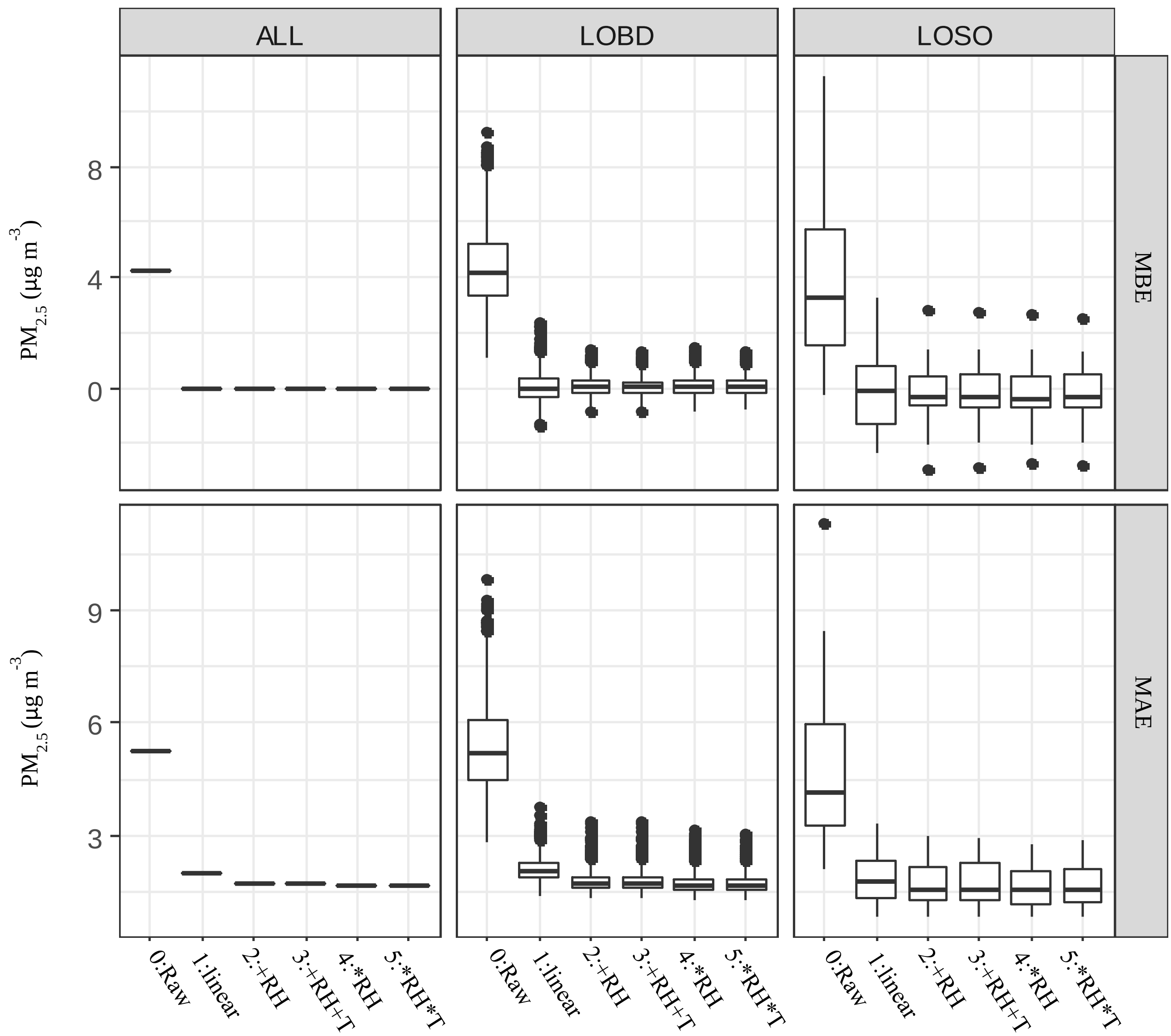

850 **Figure 4.** Performance statistics including mean bias error (MBE) and mean absolute error (MAE) are shown by correction method (0-5), where each point in the boxplot is the performance for the full dataset ("ALL"), a 12-week period excluded from correction building ("LOBD"), or a single state excluded from correction building ("LOSO").

https://doi.org/10.5194/amt-2020-413
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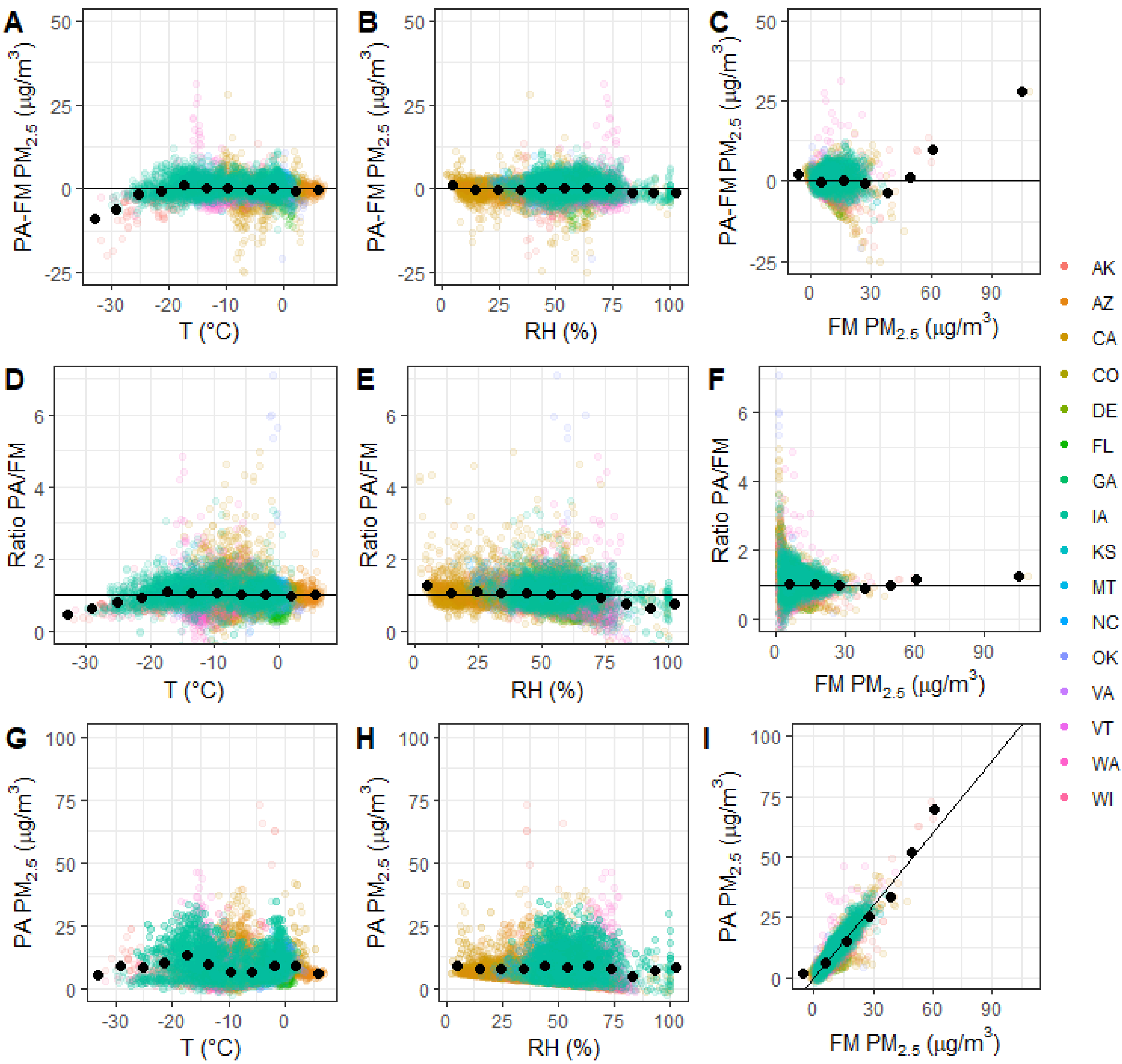

Figure 5. Error and ratio between corrected PurpleAir (PA) and FRM or FEM measurements are shown along with corrected PurpleAir $PM_{2.5}$ data as influenced by temperature, RH, and FRM or FEM $PM_{2.5}$ concentration. Colors indicate states, and black points indicate averages in 10 bins.

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https://doi.org/10.5194/amt-2020-413
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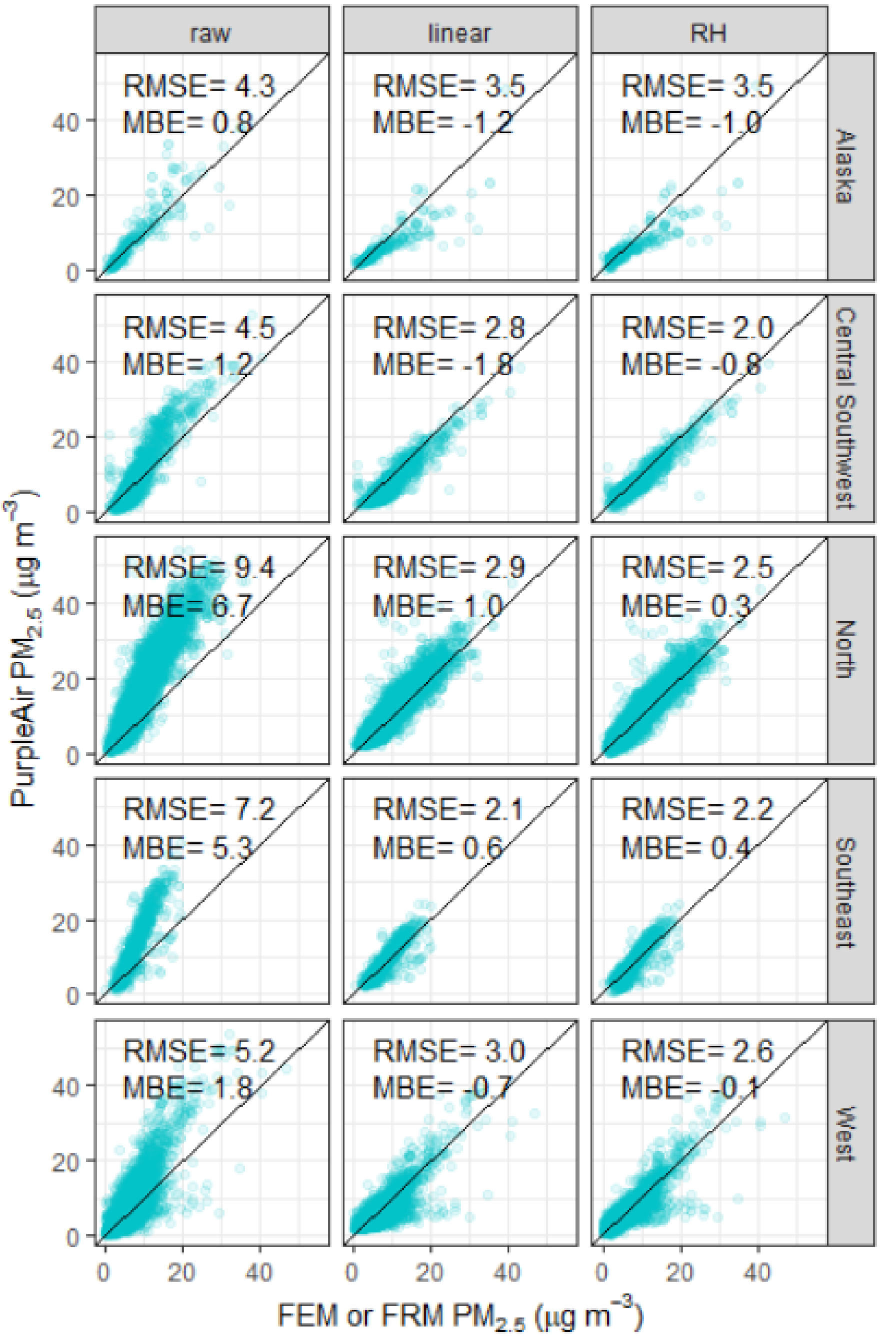

Figure 6. Scatterplot of the daily FEM or FRM $PM_{2.5}$ data with the PurpleAir data by U.S. region (see Figure 2) prior to any correction, after applying a linear correction, and after applying the final correction including RH.

https://doi.org/10.5194/amt-2020-413
Preprint. Discussion started: 2 December 2020

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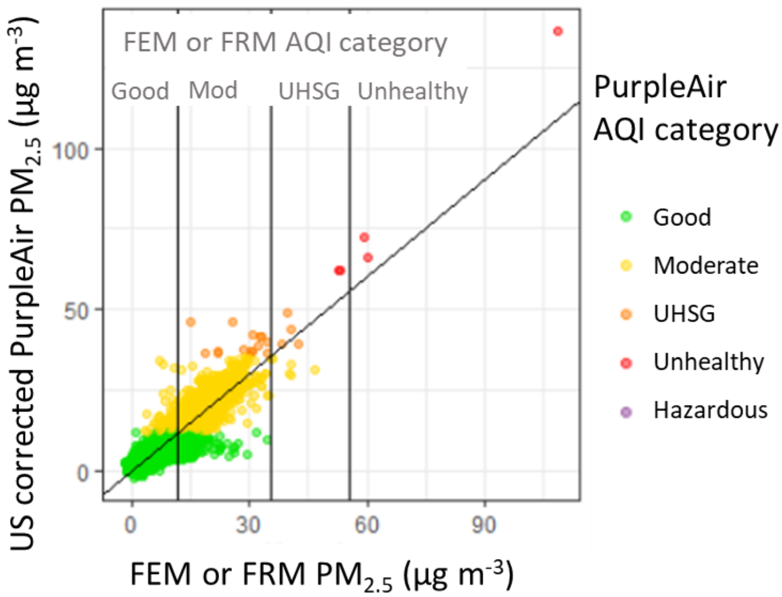

860 Figure 7. 24-hr AQI categories as measured by the corrected PurpleAir and the FEM or FRM.