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Towards a Universal Hygroscopic Growth Calibration for Low-Cost $PM_{2.5}$ Sensors

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Abstract. Low-cost particulate matter (PM) sensors continue to grow in popularity, but issues such as aerosol size-dependent sensitivity drive the need for effective calibration schemes. Here we devise a time-evolving calibration method for the Plantower PMS5003 $PM_{2.5}$ mass concentration measurements. We use 2 years of measurements from the Berkeley Environmental Air-quality and CO_2 Network sensors deployed in San Francisco and Los Angeles in our analysis. The calibration uses a hygroscopic growth correction factor derived from κ-Köhler Theory, where the calibration parameters are determined empirically using EPA AQS reference data at co-location sites during the period from 2021–2022. The parameters are found to vary cyclically through the seasons, and the seasonal cycles match changes in sulfate and elemental carbon PM composition fractions throughout the year. In both regions, the seasonal RH dependence calibration performs better than the uncalibrated data and data calibrated with the EPA's national Plantower calibration algorithm. In the San Francisco Bay Area, the seasonal RH dependence calibration reduces the RMSE by ~40% from the uncalibrated data and maintains a mean bias much smaller than the EPA National Calibration scheme (–0.90 vs –2.73 μg/m^3). We also find that calibration parameters forecasted beyond those fit with the EPA reference data continue to outperform the uncalibrated data and EPA calibration data, enabling real-time application of the calibration scheme even in the absence of reference data. While the correction greatly improves the data accuracy, non-Gaussian distribution of the residuals suggests that other processes besides hygroscopic growth can be parameterized for future improvement of this calibration.

1 Introduction

Particulate matter (PM) is a major air pollutant, presenting a significant human health concern. $PM_{2.5}$, particulate matter with diameters less than 2.5 microns, has been linked with a number of health outcomes including decreased lung function, premature death, cardiovascular diseases, and cancer (Kim et al., 2015; Cohen et al., 2017). As such, local PM observations are an essential part of a system for monitoring and improving community health and wellbeing. Additionally, coincident measurements of PM and other pollutants, like CO or NO_x ($NO_x \equiv NO + NO_2$), can be used to elicit information on urban emissions and atmospheric processes (Fitzmaurice and Cohen, 2022). The increasing availability of low-cost PM sensors has facilitated high-density PM monitoring and widespread use outside the scientific and professional air quality communities.

https://doi.org/10.5194/egusphere-2023-1701
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A well-documented issue with low-cost nephelometric PM sensors is their size-dependent and index of refraction dependent sensitivity. Specifically, the sensors are most sensitive to sub-micron particles, and sensitivity decays as particles get larger with near-zero detection for particles larger than 2 microns (Kuula et al., 2020; Molina Rueda et al., 2023; Ouimette et al., 2021). For a constant particle size distribution and composition, a single scale factor can translate the observations to those made with instruments that capture the mass of the entire size distribution. However, fixed calibrations are inadequate for temporally evolving particle size and composition distributions. One of the major drivers of variability in particle size distributions is hygroscopic growth, the uptake of atmospheric water onto PM. While reference instruments such as those used in the US Environmental Protection Agency's Air Quality System (EPA AQS) measure particles under controlled, low-humidity conditions, low-cost sensors usually measure particles under ambient atmospheric conditions (Ambient Monitoring Technology Information Center, 2022; Giordano et al., 2021). Fluctuations in the relative humidity (RH) change particle size and refractive index through water uptake, both of which impact particle light scattering and subsequent detection by nephelometers (Petters and Kreidenweis, 2007; Han et al., 2020; Hänel, 1968). On longer timescales, PM size distributions and composition vary depending on primary emissions sources and secondary PM formation pathways (Mackey et al., 2021; Sayahi et al., 2019; Stavroulas et al., 2020). An efficient calibration scheme for nephelometric sensors must therefore account for both rapid size fluctuations due to changes in humidity as well as long-term variations in particle composition and hygroscopicity.

Here, we present a calibration scheme for $PM_{2.5}$ from the Plantower PMS5003 sensor that accounts for seasonal and regional changes in outdoor PM composition and hygroscopicity. The Plantower is a widely-used low-cost PM sensor (Nilson et al., 2022; Molina Rueda et al., 2023; Barkjohn et al., 2021; Kumar and Sahu, 2021; Sayahi et al., 2019), so the development of regional, easy-to-implement corrections for these instruments is useful to air quality monitoring broadly. To our knowledge, this is the first Plantower calibration scheme to account for seasonal changes in the RH-dependence of $PM_{2.5}$ measurements.

2 Methods

The Berkeley Environmental Air-quality and CO_2 Network ($BEACO_2N$) is a high-density network of low-cost sensors spread across multiple urban centers around the globe, monitoring CO_2, CO, NO_x, O_3, and $PM_{2.5}$ (Shusterman et al., 2016). There are currently 57 active $BEACO_2N$ sites in the San Francisco Bay Area, with additional networks in Los Angeles, CA, Providence, RI, and Glasgow, UK. Each $BEACO_2N$ node contains a Plantower PMS5003 (Plantower, 2016) for PM measurements as well as an Adafruit BME280 (Adafruit Industries, 2023) for temperature, pressure, and humidity measurements. The Plantower PMS5003 is a nephelometric PM sensor reporting mass concentrations for PM_1, $PM_{2.5}$, and PM_{10}, though for the remainder of this work we will only discuss the $PM_{2.5}$ output measurement for this sensor. The sensor has internal calibrations, unknown to the user, that convert from scattered light intensity to PM mass concentrations. Here, we use the CF = ATM sensor output, which is recommended for outdoor $PM_{2.5}$ measurements. The calibration factor described herein is applied to this $PM_{2.5}$ mass concentration sensor output.

https://doi.org/10.5194/egusphere-2023-1701
Preprint. Discussion started: 7 August 2023

The humidity-dependent equilibrium water uptake by particles is often parametrized by the hygroscopic growth parameter, κ, which is dependent on particle composition. κ–Köhler theory can be used to derive an RH-dependent factor to account for hygroscopic particle growth (Nilson et al., 2022; Petters and Kreidenweis, 2007; Crilley et al., 2018), as shown in the SI. This can be supplemented by an additional scaling factor, m, that relates the RH-invariant value to a reference. This latter factor accounts for the relationship between the Plantower signal and a reference dry mass measurement.

This leads to the following calibration algorithm:

$$PM_{2.5} = PM_{plantower} * \frac{m}{1+\frac{\kappa}{100/RH-1}} \ , \quad (1)$$

which has two parameters, m and κ. For a given particle, κ can be calculated as the weighted average of the hygroscopic growth parameters for all constituents in the particle (Petters and Kreidenweis, 2007). Similarly, you could use the weighted average of this value over a sample of particles to get their collective growth parameter. However, since composition information for PM is not as widely available as total $PM_{2.5}$ mass concentration measurements, we instead determine κ and m empirically and validate their values over time using seasonal trends in observed PM composition.

The empirical parameters m and κ in Eq. (1) are calculated using co-located $BEACO_2N$ Plantower PMS5003 and EPA AQS sites, where the EPA AQS $PM_{2.5}$ provides a reference concentration for the calibration (Table 1). The fitting was performed with the Python package scipy.optimize (Virtanen et al., 2020). We describe application and evaluation of this calibration approach to the $BEACO_2N$ networks in the San Francisco Bay Area and Los Angeles, CA during the years 2021 and 2022.

In the San Francisco Bay Area, we utilize two co-location sites in the 2021–2022 period of study. These are listed in Table 1 along with a co-location site in Los Angeles, CA for 2022. Note that the Castelar ES site is located 1.06 km from EPA site 06-037-1103, whereas the two Bay Area $BEACO_2N$ sites are on-site with their respective EPA AQS reference instruments.

Table 1. Co-location sites used in this study

$BEACO_2N$ Site	Region	Co-Located EPA Site	Nearest AQS CSN Site
Laney	Bay Area, CA	06-001-0012	06-085-0005
EBMUD	Bay Area, CA	06-001-0011	06-085-0005
Castelar ES	Los Angeles, CA	06-037-1103	06-037-1103

The EPA has also developed a national Plantower calibration algorithm with the following form:

$$PM_{2.5} = 0.524 * PM_{plantower} - 0.0862 * RH + 5.75 \ , \quad (2)$$

which they currently apply to PurpleAir Plantower PMS5003 measurements on their AirNow website (Barkjohn et al., 2021). This scheme, herein the "National EPA Calibration", is used throughout the paper as a point of comparison.

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3 Results and Discussion

3.1 RH Calibration

Figures 1a and 1b show the calibration coefficients generated by fitting the observations from the Laney site (Table 1) Plantower sensor to the EPA reference data using a 4-week moving window. A strong seasonal cycle is evident. The EPA AQS Chemical Speciation Network (CSN) (sites used are listed in Table 1) provides measurements for components of PM, including the major aerosol species: ammonium, nitrates, sulfates, organic carbon, and elemental carbon (EC). Figure 1c and 1d show the sulfate and elemental carbon (EC) fraction observed at the CSN site nearest to Laney. Sulfate is the most hygroscopic of the major components of aerosols, while EC is not hygroscopic (Petters and Kreidenweis, 2007; Wu et al., 2016). For this reason, we will use these species to infer trends on the overall hygroscopicity of $PM_{2.5}$ across the seasons.

The speciation data from the nearest CSN site shows strong seasonal trends where the sulfate fraction is highest in the summers while the EC fraction is highest in the winters. The fitted κ values show an appropriate response, where the particles are most sensitive to RH in the summers and least sensitive in the winters. The scaling factor, m, follows the same seasonal cycle as κ. This can be reasoned by concluding that when κ is large, particles are subject to more hygroscopic growth, and consequently particle size distributions are shifted to larger sizes which are detected with less efficiency by the Plantower sensor.

The calibration coefficients can be smoothed, preventing overfitting, by fitting the coefficients to a sine curve. The gray lines in Fig. 1 show the sine curve fits for 2021 and 2022, where the periods of the curves are set to 1 year. Application of Eq. (1) using these smoothed κ and m parameters is herein referred to as the "Seasonal RH Dependence Calibration". This calibration is applied to the data over 2021 and 2022. Figure 2 shows a timeseries of the pre- and post-calibration sensor data, along with the EPA AQS reference measurements. Table S1 shows that the calibrated data has a significantly improved Pearson's correlation, r, and NRMSE, especially during the winter months.

https://doi.org/10.5194/egusphere-2023-1701
Preprint. Discussion started: 7 August 2023

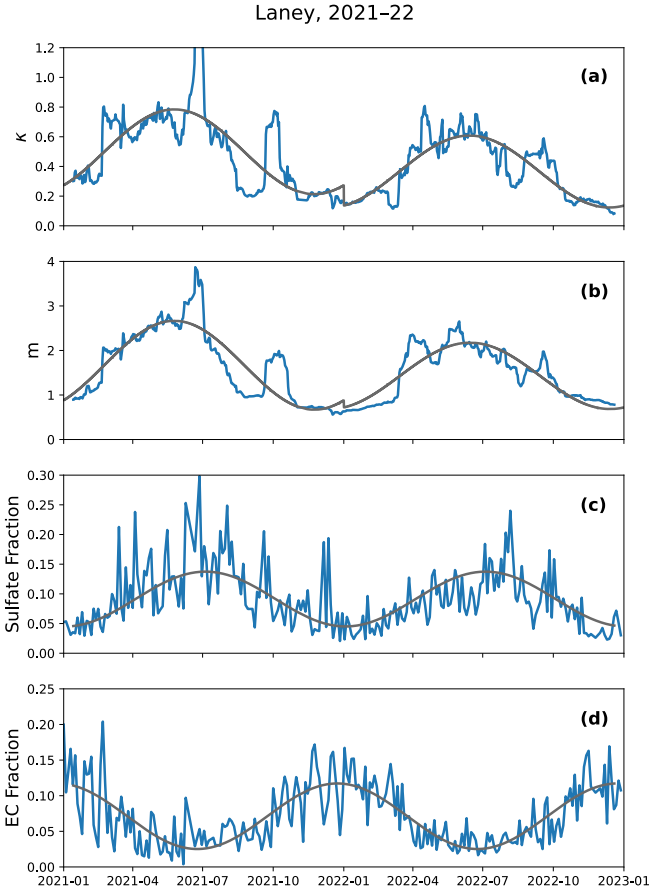

Figure 1. (a,b) Calibration parameters generated for Laney site, and (c,d) particle speciation data from the nearest EPA AQS CSN site.

https://doi.org/10.5194/egusphere-2023-1701
Preprint. Discussion started: 7 August 2023

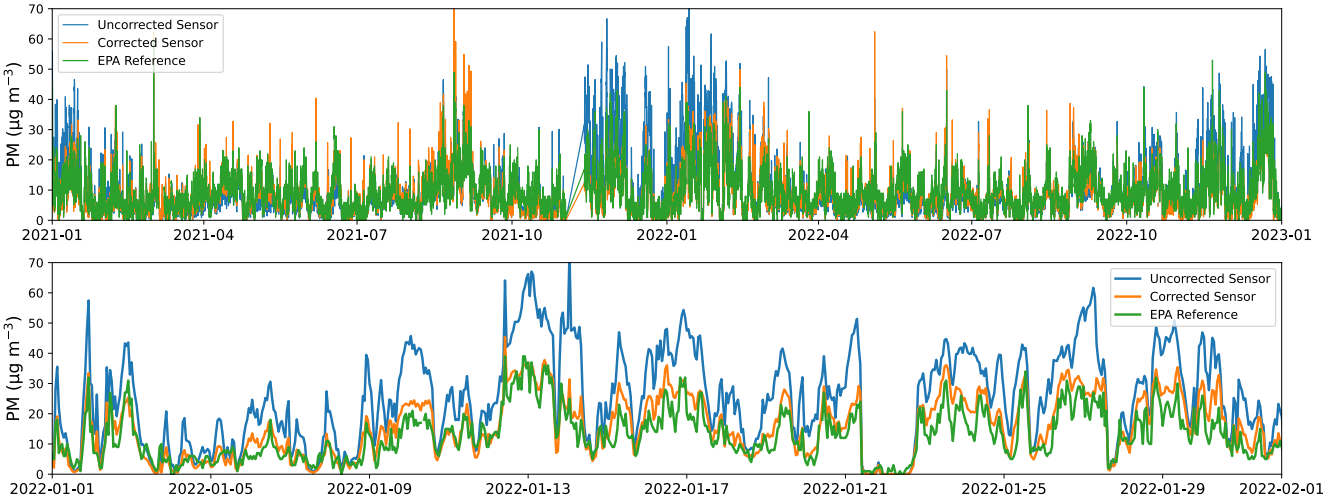

Figure 2. Timeseries of the Laney site Plantower $PM_{2.5}$ data without and with the seasonal RH dependence calibration, compared to the co-located EPA $PM_{2.5}$ reference data for the whole two year study period (top) and for the subset of January 2022 (bottom).

3.2 Evaluation

Figure 3 shows that the strong RH-dependent bias in Plantower PMS5003 outputs is removed through the implementation of the seasonal RH dependence calibration scheme. Notably, the national EPA calibration scheme, which assumes a linear RH-dependence, does not properly account for the non-linear RH effects on particle size and detection. Figure S1 shows that the seasonal RH dependence calibration also removes the temperature dependence of the residuals. This was expected since most of the temperature dependence was likely due to covariance of temperature and RH rather than intrinsic temperature effects on sensor measurement or performance. Figure 4 shows the uncalibrated and calibrated Plantower measurements compared to the EPA AQS reference observations for the entire two-year period. Both the National EPA calibration and the seasonal RH dependence calibration led to reductions of ~40% in the RMSE and increases of ~0.75 in the coefficient of determination (R^2), but the EPA national calibration introduces a large negative bias in the measurement.

https://doi.org/10.5194/egusphere-2023-1701
Preprint. Discussion started: 7 August 2023

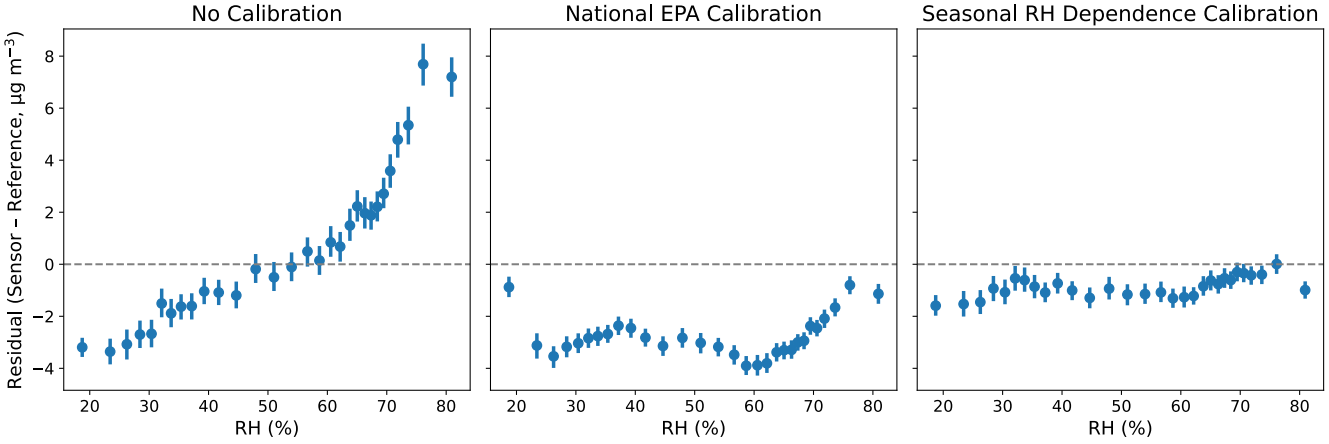

Figure 3. Measurement residuals (sensor output – EPA AQS values) for data from the Laney site with different calibration algorithms, binned into 30 RH bins.

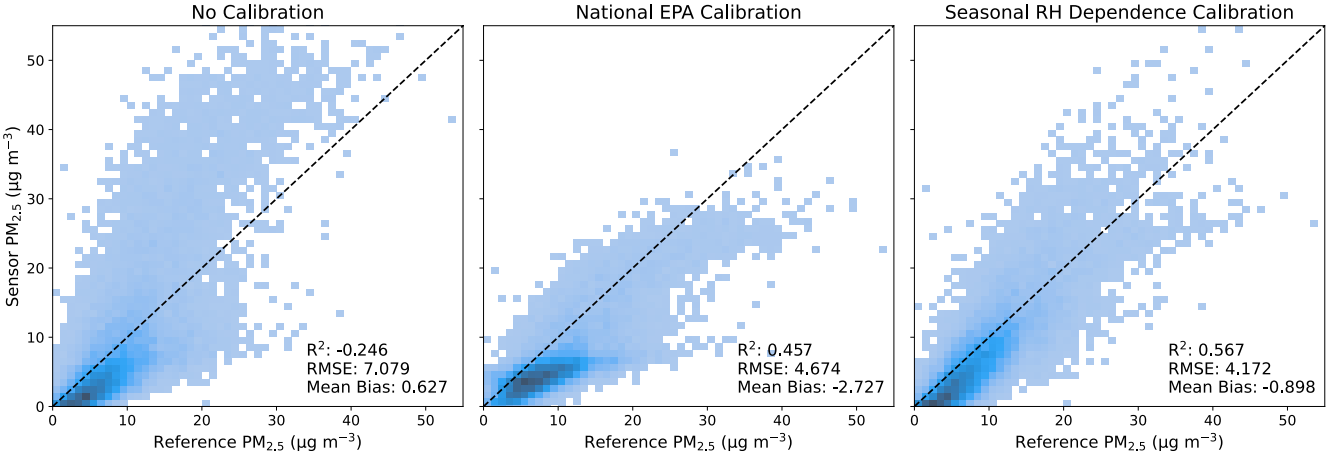

Figure 4. Sensor predicted PM2.5 values versus EPA reference values for Laney site from 2021–2022 with different correction algorithms. Performance metrics are the Coefficient of Determination (R^2), root-mean-square error (RMSE), and mean bias.

Analyzing the distribution of errors from each of the calibration types under different mass concentration and humidity levels can help assess the completeness of each of the calibration schemes. We would expect that a complete calibration would produce zero-centered, Gaussian error distributions since all remaining errors would be from random noise in the measurement. Looking at the distribution of errors at different $PM_{2.5}$ mass concentrations (Fig. 5) it is evident that, while the seasonal RH dependence calibration produces errors more symmetric and centered near zero than the uncalibrated data and the EPA calibration data, the errors are still not perfectly Gaussian, especially when the $PM_{2.5}$ mass is high. This suggests that there are other physical processes at play unaccounted for by this calibration. We also explore the error distributions when κ and m are not smoothed to sine waves and find no meaningful differences between the smoothed and unsmoothed

https://doi.org/10.5194/egusphere-2023-1701
Preprint. Discussion started: 7 August 2023

cases when $PM_{2.5} \leq 20$ µg m^{-3}, which accounts for over 95% of the data (Fig. 5). As such, representing seasonal changes of κ and m throughout the year as sine waves is a valid approximation.

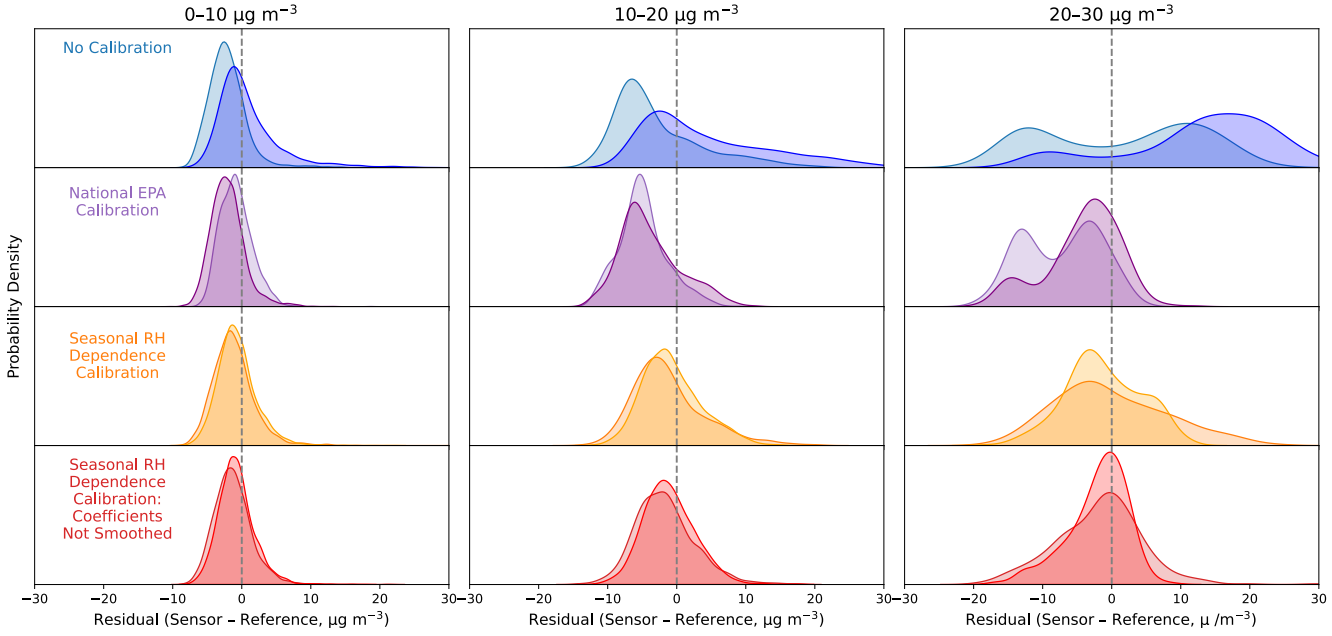

Figure 5. Sensor residual distributions for different calibration schemes at different $PM_{2.5}$ mass concentration bins for RH < 50% (light color) and RH > 50% (dark color) conditions. The calibration scheme "Seasonal RH Dependence Calibration: Coefficients Not Smoothed" uses the calculated κ and m values as-is, without smoothing to a sine wave.

3.3 Inter-Region and Intra-Region Comparisons

Given that the κ and m parameters follow trends consistent with PM speciation data, it is reasonable to assume that the parameters generated at one site can be applied to nearby sites if the particle composition is homogenous across the urban area.

To further test this assumption, we independently generate calibration coefficients for another Bay Area co-location pair at the EBMUD site (Table 1). As seen in Fig. S2, the EBMUD and Laney co-location pairs independently reproduce nearly identical calibration coefficients, ensuring that the coefficients are not over-fit on one site but rather reflect regional trends in PM composition. Another concern is the possibility that individual sensors have disparate sensitivities or offsets. We find that uncalibrated measurements from 10 co-located Plantowers show strong agreement with each other (Fig. S3), with differences between sensors generally less than 1 µg m^{-3}, suggesting that there is little sensor-to-sensor variability in sensor performance.

The seasonal RH dependence calibration scheme was tested in another urban area to ensure its generalizability beyond the Bay Area. Using a co-location site in Los Angeles, CA, we find that the aerosol composition again displays seasonality (Fig. 6), with the sulfate fraction highest in the summers and the EC fraction highest in the winters. In Los Angeles, as in the Bay

https://doi.org/10.5194/egusphere-2023-1701
Preprint. Discussion started: 7 August 2023

Area, the trends in κ and m match the composition variations. κ and m are largest in the summers when the particles are the most hygroscopic, and smallest in the winters when the particles are the least hygroscopic. The seasonal RH dependence calibration outperforms the national EPA calibration and the uncalibrated data, with a higher coefficient of determination and lower RMSE (Table S2).

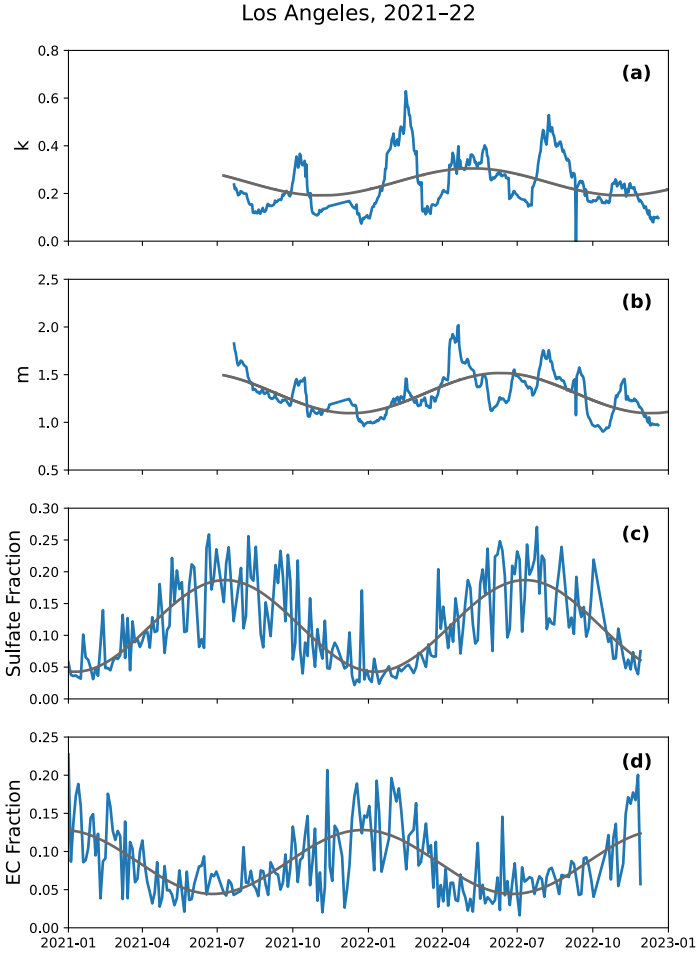

Figure 6. (a,b) Calibration parameters generated for the Los Angeles site, and (c,d) particle speciation data from the nearest EPA AQS CSN site.

3.4 Real-Time Application of the Calibration

Since the calibration coefficients generated in Fig. 1 and Fig. 6 are periodic and aerosol composition and its seasonal variation are changing slowly from year to year, it is possible to apply the seasonal RH dependence calibration to sensor measurements in real-time without the need for EPA reference measurements to be real-time as well. We test the validity of this approach by generating sinusoidal calibration coefficients in 2021 and projecting them forward 6 months into 2022 without using the 2022 reference data, as shown for data at the Laney site in Fig. 7. Like before, both the seasonal RH

https://doi.org/10.5194/egusphere-2023-1701
Preprint. Discussion started: 7 August 2023

dependence calibration and the national EPA calibration led to significant reductions in the RMSE (~40%), and the national EPA calibration produces a significant negative bias (–2.39 µg/m^3, compared to 0.98 µg/m^3 in the seasonal RH dependence calibration). Thus, in regions with strong and stable seasonal cycles for PM composition, the sinusoidal parameters can be applied in the months following the period in which they were generated with reasonable accuracy.

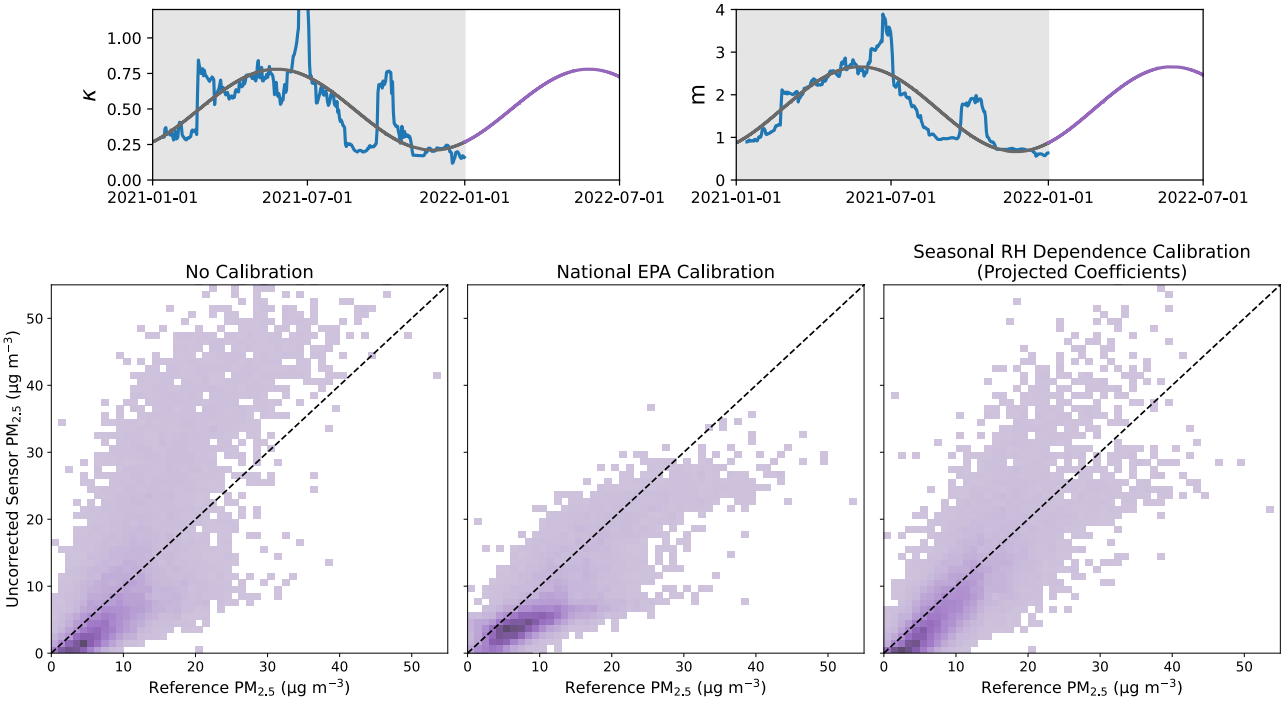

Figure 7. (top) κ and m parameters calculated at the Laney co-location site in 2021 with sinusoidal fits projected 6 months into 2022, and (bottom) sensor predicted PM2.5 values versus co-located EPA reference values for the Laney sire for Jan–Jun 2022 with different calibration algorithms.

4 Conclusions

The Plantower seasonal RH dependence calibration is aimed at addressing biases in sensor measurement caused by changes in the size distribution of PM, largely from fluctuations in relative humidity leading to hygroscopic growth and seasonal changes in particle composition that affect hygroscopicity. We provide a physically meaningful calibration scheme that is simple to define and implement for multiple regions in the United States. The seasonal RH dependence calibration utilizes only RH as an additional parameter and has calibration coefficients that reflect seasonal changes in PM speciation. This method provides a time-variant calibration scheme that can be implemented in real-time due to the periodic nature of the calibration coefficients. Speciation data provides insight and validation to the calibration parameters but is not needed in creating the calibration. Additionally, analysis of multiple co-location pairs in the Bay Area show that the calibration

https://doi.org/10.5194/egusphere-2023-1701
Preprint. Discussion started: 7 August 2023

parameters are generally uniform within a given region, and as such this calibration can be generated for many sites using limited co-location pairs if there is reasonable confidence that aerosol speciation is uniform across the application area.

It is worth noting that the seasonal RH dependence calibration assumes regular seasonal changes in particle composition, and as such lacks utility during extreme events that require unique corrections, as is the case when measuring wildfire smoke or dust events (Holder et al., 2020; Kaur and Kelly, 2022). The seasonal RH dependence calibration is being actively applied to the $PM_{2.5}$ measurements in the $BEACO_2N$ network, which are publicly available and can be found on their website (beacon.berkeley.edu).

5 Code and Data Availability

Data and code used in this paper are available at the following GitHub repository: https://github.berkeley.edu/milan-patel/Plantower-Calibration-Paper. Data from the $BEACO_2N$ network (beacon.berkeley.edu) and the EPA AQS network (epa.gov/aqs) are also publicly available online.

6 Author Contribution

MYP, PFV, and RCC conceptualized the work. MYP completed the formal data analysis and coding. MYP wrote the original draft, and PFV, RCC, JK, and WMB reviewed and edited the draft. RCC provided supervision for the project.

7 Competing Interests

Ronald C. Cohen is an associate editor of *Atmospheric Measurement Techniques*.

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